Artificial Intelligence Planning Techniques for Emulating Agents with Application in Social Services

by

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Abstract

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This thesis investigates the problem of emulating seemingly irrational behaviour with the use of a rational reasoner. This thesis adopts the position that human behaviour is rational but our reasoning process is bounded. To an observer with an equally rational reasoning process but different bounds, an agent's behaviour may seem irrational. The approach presented in this thesis extends a rational reasoner in classical artificial intelligence planning, STRIPS, using three theories from psychology and economics. The first theory, bounded rationality, limits an agent's reasoning ability with human-like bounds. The second theory is Maslow's hierarchy, which is used to organize and rank an agent's goals during the process of plan creation and execution. The third theory is the emotional cycle of change which is used as a nonlinear measure of expectation of success, triggering goal reranking and replanning processes during plan execution.

By adopting these methods, human behaviour emulation is viewed as a classical planning problem with a non-linear evaluation function. The resulting system, **B**ounded **R**ational **A**gent **M**otiv**A**tions framework (BRAMA), emulates trajectories of agent behaviour. The trajectories simulate agent usage patterns for various services to meet the agent's goals. The target application of BRAMA is in social services, simulating the response of homeless clients to the Housing First intervention program in Calgary, Canada. The results of the simulation can be used by policy makers to evaluate the effectiveness of alternative programs before they become policy.

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Chapter 1

Introduction

This thesis provides a reasoning mechanism that is capable of emulating behaviour of a homeless client as they interact with service providers. The central hypothesis is that seemingly "irrational" behaviour can be emulated using a rational reasoner. The motivating application of this thesis is the evaluation of social service policies using a simulation. To evaluate a social service policy using a modelling approach, we must:

- model service delivery, and
- model client behaviour in response to a new intervention program.

However, as will be discussed in Section 1.1, policy makers in the area of social service delivery do not have good tools for evaluating the effectiveness of alternative programs before choosing one as part of a policy. Instead, policy makers operate under three main assumptions [154, 236, 131].

1. All necessary information about service providers and their clients required to make a decision is known, or that the uncertainty is well understood.
2. Any changes required to implement the new policy to a broader population of clients can be made.
3. Any clients that respond to the new policy in a way that cannot be accurately anticipated or emulated are acting irrationally.

The research question addressed by this thesis is:

> Given a bounded observer (the policy maker), can seemingly "irrational" behaviour of bounded subjects (clients) be emulated using a rational reasoner?

The process of social service delivery can be modelled using existing system modelling techniques [259, 195]. It is also possible, to a certain degree, to predict how resources might be managed during service delivery with the use of a simulation [106]. What is missing is the ability to model and predict the impact an intervention program will have on the targeted homeless population.

Before moving forward, a clear distinction must be made between emulating and simulating social service clients, specifically as it relates to people who are homeless. *Simulation* of a client is the replication of their environment and how they interact with it, capturing the macro view of the interactions [78, 107]. The simulation environment contains both agents being emulated and the environment they interact with. *Emulation* is concerned with modelling human decision making and reasoning processes such that the execution of this model within a simulation replicates how the decision maker being modelled would make decisions [231]. An emulation is based on a high-fidelity model that considers deterministic factors and mechanisms controlling an individual's decisions [245]. Simulation models that don't use emulation are generally of low fidelity, based on probabilities that an individual will choose one decision over another. These probabilities are based on past policies and may not be applicable under a proposed policy being evaluated. Simulation models that use emulation are based on psychological theories of decision making that are more robust than their probabilistic counterparts [173].

1.1 Problem of Homeless Client Emulation

During an initial investigation into social service evaluation, it has become apparent that the least represented part of systems in use today are the clients themselves. A key difficulty of representing clients is their seemingly "irrational" behaviour in response to well-planned and structured intervention programs. Before a client can be emulated, their behaviour must be understood sufficiently enough to be reproducible. Hence, the focus of this thesis has been to explain this "irrationality" in a way that can be understood through existing models of human behaviour by creating a high-fidelity client emulation model.

There are two major and interrelated factors contributing to the difficulty in modelling behaviour of homeless clients. First, there is insufficient data that captures the unique and dynamic lives of service clients, especially the homeless population [269, 184, 188, 247, 7]. The missing data must describe factors impacting client behaviour, and be suitable for model calibration for different sectors of the client population. Second, the homeless population is notoriously difficult to make predictions about [111, 257, 76, 2]. Structural factors are often unknown, undocumented, or under-reported. Internal factors for transient populations are often difficult to establish, while negative influences are often under-reported.

1.1.1 Homeless Data Collection and Analysis

Understanding the behaviour of social service clients has been an active research area. However, the lack of data is a fundamental limitation of social service studies. Contributing factors are the irregularity of participants living in desperate circumstances, transient means of survival, and the ethical dilemmas on the part of researchers who must often make special arrangements for individuals, jeopardizing the integrity of the study [76].

Current research uses information gathered about the characteristics of people living in poverty, setting the empirical and theoretical foundation for simulating this population. Much of this work initially focused on gathering and measuring the progress and satisfaction of clients within different intervention programs. Due to the difficult nature of tracking and interviewing clients, the majority of initial data collected was based on administrative data obtained by the same organizations being evaluated [269, 184]. As a result, reliability of the data was reduced and there was a lack of detail about experiences of the clients.

Studies often limit their scope of client characteristics to the success rates attributed to program-specific factors, controlling for or ignoring other factors [188, 247, 7]. After positive outcomes, follow-up studies are required to focus on the impact the same programs have on newly targeted populations where specific client factors are investigated [138, 46, 2]. As a result of this work, an increasingly client-focused model of behaviour has developed, focusing on client coping strategies, physical and mental health, transient lifestyle, and spending habits [267, 55, 42]. Structural determinants have also been identified, such as the relationship between poverty and neighbourhood characteristics, neighbourhood mobility, distribution of resources, demotivational events, and environmental constraints [165, 92, 49, 48, 64].

With the collection of more data, a new picture of clients has begun to emerge that moves away from common negative stereotypes and toward the real impact that constrained resources and conflicting needs have on their lives [55, 247]. However, without a more granular representation of a client's decision process, their behaviour seems irrational or self-defeating [154, 236, 131]. Lack of such details prevents the development of a client model that can predict the true progress of clients in an intervention program.

1.1.2 Homeless Client Emulation

Relying on the available data on the structural and socioeconomic factors impacting homelessness, policy makers can rely on high-level simulations and low-fidelity models based on historical data [156, 68, 88]. However, such low-fidelity models can produce paradoxical recommendations that may seem productive from one perspective but not another. For example, relying on a low-fidelity model focusing only on housing needs of individuals, Early (1999) showed how weakening building codes and increasing low-quality rental housing would encourage individuals to stay in higher-quality housing [68]. Such housing, however, may not be a good long-term investment for the city. Equally, city-level studies fail to capture individual-level factors, resulting in different conclusions for studies at different levels of abstraction [181].

1.1.3 A New Approach

What is largely missing from existing literature is a high-fidelity model of human behaviour that, according to existing theories, can emulate seemingly "irrational" behaviour exhibited by a client. Such a model should focus on individual clients and their decision-making process, and how that behaviour affects and is impacted by their circumstances, means, and needs [76, 249]. The limitation is not technological per se. Many simulation packages are capable of modelling psychological factors in human agents, while others focus on human decision-making processes. Many economic and sociological theories focus on actions of individuals but make assumptions about rationality that are not applicable to or reflected by data on the homeless populations [274, 271]. As a result, any behaviour not reproducible by such models may be viewed as "irrational."

The model developed here assumes human behaviour is rational but the reasoning process is bounded. To an observer with an equally rational reasoning process but different bounds, this behaviour may seem irrational. This thesis extends a rational reasoner in classical artificial intelligence planning, STRIPS, using three theories from psychology and economics. The first theory is bounded rationality, which is used to limit the reasoner with human-like bounds [226]. The second theory is Maslow's hierarchy, which is applied in organizing and ranking an agent's goals during the plan creation and execution processes [160]. The third theory is the emotional cycle of change (ECOC) which is used as a nonlinear measure of expectation of success, triggering goal reranking and replanning processes during plan execution [129].

By adopting these methods, human behaviour emulation is viewed as a classical planning problem with a nonlinear evaluation function. The resulting system, **B**ounded **R**ational **A**gent **M**otiv**A**tions framework (BRAMA), generates trajectories of agent behaviour. The trajectories are used to emulate an agent's usage patterns for various services to meet its needs.

The target application of BRAMA is social services, simulating the response of homeless clients to homeless intervention programs. The results of the simulation can be used by policy makers to evaluate the effectiveness of alternative programs before they become a policy. As with other systems in this domain, the evaluation of results produced by BRAMA are limited by the data available about homeless clients.

1.2 Requirements for a High-Fidelity Client Emulation

What is a high-fidelity model of human behaviour? Fidelity is defined as "a measure of realism of a model or simulation" [99]. Fidelity can characterize the representation of a model, a simulation, the data used by a simulation, or an exercise. Each fidelity characterization can have different implications specific to an application domain.

Reviewing the social service system in Section 1.1, several key insights about the homeless population highlight what is required to create a suitable high-fidelity simulation, as well as its potential limitations [90]. Often people experiencing homelessness are perceived through the filter of social norms by the general population. At the same time, they face different constraints than the rest of the population in their society, and live by different social norms. To an outside observer, their life choices may seem irrational, incompatible with society, and detrimental to their own wellbeing. Traditionally, large-scale simulations have been used to try and close the gap between program trials and implementation of a complete policy. Based on the population's decisions under past policies, probabilistic models capture a variety of factors that reveal motivations and preferences. Missing factors are supplemented by social science models which may rely on social norms and structural factors more relevant to the general population.

These approaches, however, are insufficient to create a high-fidelity model of social service clients. Models need the ability to react to new policies similarly to clients, not past policies. Social science models are not always applicable due to different social norms. The complete set of requirements for creating a high-fidelity model of clients and service providers in the social service chain are briefly described next.

The fidelity of behaviour simulation incorporates different representations of domain constructs. Low fidelity representations rely on short qualitative descriptors such as "low," "medium," or "high." Mid-fidelity representations rely on shorthand descriptions that include several attributes that exist in the real object being represented. High-fidelity representations rely on long descriptions of constructs identified as significant to a particular domain, and incorporate multiple attributes to represent those constructs. High-fidelity descriptions also incorporate some type of enumeration of attribute values, specify the quality of attribute representation, or both. The quality of attributes can be based on any combination of attribute accuracy, error, fitness, precision, resolution, sensitivity, tolerance, and validity [99].

To create a high-fidelity client emulation model, we must take a systems view of the social service provisioning process, considering service providers and the clients that flow through that system. From an industrial engineering systems perspective, social services can be seen as a social services chain (SSC), a network of services through which clients flow. Using industrial engineering techniques, metrics can be developed that "enhance the effective and efficient planning and delivery of services" [21]. An important part of the SSC is capturing the clients moving through the system, their needs, and metrics for how well those needs are being satisfied [90].

This thesis assumes that people are goal driven, hence rely on a *teleological* reasoning process, which includes goals, expectations, subgoals, goal temporality (short- versus long-term goals), and planning. Closely linked to goals are the *constraints* faced by homeless clients that prevent goals from being satisfied, and include structural (environmental and organizational) and social (friends, family, etc.) constraints. Psychological constraints, like addiction, are considered as cognitive bounds that limit a client's decision making process. A client's *rational decision making* is based on the economic notion of a *rational agent* that maximizes its utility function. We assume that clients are able to learn from their experience by adjusting their behaviour in response to services provided.

A *service provider* faces a number of limitations that include the requirement of providing a certain level of quality of service and availability of resources. A provider is represented as a set of service specifications, effectiveness metrics, constraints, and accountability measures. A client simulation must have the ability to model and instrument service delivery *processes* explicitly. *Societal* constraints and accountability factors also have an impact on client behaviour, and must be represented. While any human interactions are innately social, here we focus on those that specifically include social needs of the client and social norms imposed by society.

1.3 Thesis Summary

This thesis provides a review of the emulation problem and introduces the proposed model. A number of applicable theories of decision making are evaluated for their ability to emulate human-like agents. The fidelity of the proposed model is incrementally increased along with the BRAMA framework by extending each decision theory to include human-centric factors. A new ontology is developed that grounds the model's configuration in data about participants in an intervention program. The ontology identifies, characterizes, and ranks needs of participants captured by the data. Finally, the BRAMA framework is evaluated on its ability to emulate behaviour of program participants as they interact with service providers.

1.3.1 Human-Centric Single Decision Making

Developing an architecture capable of emulating rational human behaviour requires an expectation utility function that incorporates human-centric factors. Chapter 3 of this thesis begins by introducing the BRAMA framework, which extends single decision theory (DT) by including human-centric factors impacting behaviour. A utility for individual decisions made by an agent is calculated that incorporates relevant social science and economic theories.

The first extensions are information and memory bounds, as defined by bounded rationality (BR) [226]. The BR extension explicitly defines missing information about the actions available to an agent, as well as all possible goals that satisfy its basic needs. The memory bound limits the amount of information an agent can store. The second extension, based on Maslow's hierarchy (MH), grounds an agent's basic needs to tangible goals, providing a grouping and ordering developed in the field of psychology [160]. Basic goal semantics are introduced to map an agent's expressed goals to the MH levels. BRAMA has the ability to calculate ordinal and cardinal goal utility for goals mapped to MH levels, relying on the initial order of goals preferred by the agent (ordinal utility) as well as the ratio of satisfied goals to outstanding goals (cardinal utility). The third extension is an expectation utility function that incorporates emotional factors impacting the human decision-making process. An emotion-based function from organizational psychology, the ECOC [129, 67, 143, 159], adapted for behaviour of homeless clients, is contrasted against an expectation utility function from neoclassical economics that assumes human decision making is modelled after the rational agent theory [274, 271].

1.3.2 Human-Centric Sequential Decision Making

Like the agent, the observer's reasoning is also limited by bounded rationality. As a result, the observer is not aware of all factors impacting an agent's decisions. Instead, it would be more realistic to calculate the utility of all *observable* decisions an agent makes. Unfortunately, single DT is not capable of calculating and comparing a set of decisions over time, as it assumes decisions are independent of each other. In Chapter 4, the utility calculated by BRAMA is extended using sequential decision theory. Sequential DT provides the theoretical foundation for representing and calculating the utility of a sequence of decisions an agent makes over an extended period of time. The new utility also allows an observer to compare such sequences to determine which one maximizes an agent's utility.

A sequential DT model represents behaviour as a decision tree. The tree includes all choices an observer thinks are reasonable choices for an agent to make to satisfy the agent's goals. Each path in a decision tree represents a sequence of choices an observer believes an agent may intend to make. The observer constructs a decision tree bounded by its own limited information, memory, cognitive abilities, and time. Once constructed, the agent uses various decision strategies to reason about available sequences and goals within its own bounds. An agent has the same bounds as an observer but is more restricted by them. To compensate for its limitations, an agent has multiple decision strategies defined by dynamic choice theory that guide its reasoning process, including myopic, sophisticated, and resolute. Each strategy is characterized by the potential to accept risk and the ability to recalculate utility of future states.

BRAMA extends the goal utility calculation by incorporating an enhanced cardinal goal ranking. Based on the initial goal order used by single DT, the new calculation also considers the order in which MH level goals are satisfied in the sequence. This provides a goal utility that considers a goal's position relative to other goals in the sequence. The utility calculation also incorporates ECOC, adopting definitions from the single DT extension.

1.3.3 Human-Centric AI Planning

A decision tree created by sequential DT represents reasonable choices an agent can make provided the agent is guided solely by one of the decision strategies defined by dynamic choice theory. Human behaviour, however, is also impacted by external factors that a bounded observer may not be aware of. What is needed is a representation that captures the sequences of choices that are not subjectively inferred from an agent's characteristics. Such sequences must not only rely on whether an agent's presumed preferences and goals warrant such choices, but also include factors the agent may not be aware of.

In Chapter 5, the BRAMA agent's reasoner is extended to include an AI planning algorithm capable of generating all possible combinations of choices, within bounds imposed on the agent's reasoning abilities. AI planning represents sequences as a search tree, a more robust representation than a decision tree as it includes all combinations of actions that are objectively possible from the perspective of the agent. Each sequence of actions an agent can make is independent of an observer's limited perception of the agent. Axioms defined for various extensions of decision theory are evaluated to identify those axioms that are preserved in the new extension to BRAMA and those that are not. The BRAMA framework incorporates a planner called STRIPS (STanford Research Institute Problem Solver) that considers all available and possible actions to generate a plan, guided only by the agent's outstanding goals. BRAMA then extends STRIPS to a human-centric planner called STRIPS-BR.

Unlike existing planners, STRIPS-BR explicitly defines how the information, cognition, and time bounds limit the agent's reasoning process. It also uses the human-centric utility function based on Maslow's hierarchy and ECOC. By extending a planning algorithm, BRAMA agents can respond to unexpected consequences of their actions, caused by bounded rationality and emotional evaluation of plans. By monitoring plan execution and replanning when needed, the agents are able to adjust plans, correcting for any errors in their initial perception of internal and external factors.

1.3.4 Ontology of Client Needs and Social Services

Human motivations have long been credited with influencing decision making [12, 86, 58]. This created an opportunity for social service practitioners to use a client's own motivations to promote constructive change in their behaviour [135, 218, 243]. However, due to the unique circumstances and life experiences of homeless clients, practitioners must rely on "whatever works" to assess and modify client behaviour [35]. To assess a client's current state, questionnaires such as the "Service Prioritization Decision Assistance Tool" (SPDAT) measure their "vulnerability index" based on past and current circumstances. Next, need-assessment forms are administered every tree-month to asses client needs. Once a client's state and outstanding needs have been identified, techniques like motivational interviewing and acceptance as well as commitment therapy are used to facilitate change in the client's behaviour that aligns with their motivating factors [35].

Chapter 6 introduces an ontology used to capture the needs, constraints, and services required to create a high-fidelity homeless client emulation. The ontology engineering methodology is used to engineer and evaluated the Ontology of Social Service Needs (OSSN). OSSN is the first ontological representation of the social service domain from the perspective of the client, with a focus on their needs rather than the efficiency of the service provider. The ontology presented here is developed using the dataset for Calgary Homeless Foundation (CHF) participants in a Housing First (HF) program.

1.3.5 Evaluation

One of the objectives of this work is to identify factors that are observable by a bounded observer and can be used to emulate seemingly "irrational" behaviour using a rational reasoner. During the simulation process, a BRAMA agent emulates behaviour of social service clients modelled by the CHF data. Chapter 7 undertakes this work and evaluates the performance of a BRAMA simulation. The agent behaviour is simulated with different agent model configurations. Each configuration results in simulated trajectory as agents interact with social services. The simulated behaviour is measured on how well it matches the actual trajectories exhibited by CHF clients.

The results of the experiments indicate that some form of replanning is required to emulate changing needs of clients. Several mean absolute errors (MAE) were used to evaluate proper cutoff thresholds for acceptable models. Acceptable models were those that produced simulated trajectories that matched actual trajectories in the data with high accuracy. Factors used in configurations that produced more accurate and stable models increase the fidelity of BRAMA's agent model.

1.4 Conclusion

The contributions of this thesis are in three areas: AI search, representation, and emulation of social service clients. In the AI search area, a planning algorithm extends an existing algorithm with human-centric features. This work includes:

- Evaluation of applicable decision theories and their limitations.
- A framework for emulating seemingly "irrational" behaviour grounded in decision theories.
- Explicitly defined limitations based on bounded rationality.
- Goal ordering and utility calculation grounded in Maslow's hierarchy.
- Utility calculation based on the emotional cycle of change.
- Replanning algorithm to overcome bounded rationality with the use of emotional thresholds.
- Human-like goal reasoning.

In the representation area, an ontology of social service client needs is created based on goals expressed by participants in a real-life intervention program. The ontology captures basic needs, explicit goals, initial goal ranking expressed by clients, and constraints preventing clients from satisfying their goals. A domain-specific mapping is made between client needs and Maslow's hierarchy, grounding goal ranking in a psychological theory of needs. The ontology also captures the resources and services offered by service providers that relieve the constraints faced by clients.

The contribution to social services is the first client-focused ontology of the social service system. The objective is to capture how certain client populations will react to an intervention program. By focusing on the clients, they are presented as rational beings, with a unique set of constraints that may lead an observer to mischaracterize rational behaviour as "irrational." Finally, the ontology makes an explicit distinction between services offered and social programs that administer them. This allows a program administrator to track the outcomes of participants independently from service providers.

Chapter 2

Background

2.1 Introduction

The objective of this thesis is to create a high-fidelity emulation model of human behaviour. Towards this goal, the research questions outlined in Chapter 1 address the difficulty in distinguishing between rational and irrational behaviour, and whether a computational agent can emulate apparently irrational behaviour using a rational reasoner. The approach presented in this thesis is framed in the context of homeless client behaviour perceived as irrational by an outside observer.

This work assumes human behaviour can be modelled by goal-driven agents that make decisions about actions towards satisfying goals, and that those decisions span over an extended period of time. From this perspective, behaviour can be represented as a sequence of actions called a trajectory. The target population of this work are social service clients, a historically difficult population to evaluate [111]. Available information about this population is limited to conclusions about high-level observations and theories about homeless client behaviour. The conclusions are based on either an aggregate dataset that focuses on factors targeted by the study or individual interviews capturing the constraints and life experiences of a small number of individuals. Having limited understanding about the decision making process of an entire homeless population, this thesis focuses on observable aspects of client behaviour rather than individual choices made by specific individuals. The methodology presented here combines theories from social science and economics with methods from artificial intelligence to create a high-fidelity human-centric model of behaviour.

Human behaviour has been studied extensively by different branches of social science. Artificial intelligence (AI) methods that either simulate behaviour or perform tasks traditionally assigned to humans have been heavily influenced by social science, hence the two fields are linked in many ways.

Social sciences, economics, and AI share a general consensus on what is required to understand human behaviour. All these fields require the same five main components:

Goals: What an agent wants to be true.

Means: How goals will be satisfied.

Constraints: Factors preventing goals from being satisfied.

Rational means: Optimal means of satisfying goals.

Non-rational means: Non-optimal means of satisfying goals.

This chapter introduces each component in the context of homeless client decision making. Specifically, it focuses on constraints that impact the ordering of goals and selection of means by a social service client. Special focus is placed on the external environment and internal limitations of the client [90].

While there is multidisciplinary research that spans one or more of these disciplines, each discipline focuses on different types of analysis under different assumptions about human behaviour. Economics and AI focus on prescriptive and predictive analysis that assume an agent's method for organizing means to achieve goals is rational. Any identified discrepancies between behaviour models and observed behaviour are adjusted away with inductively derived probabilities and known cognitive biases. Sociology and psychology, by contrast focuses on descriptive, diagnostic, and predictive analysis, making no assumptions about an agent's reasoning process. Here, analysis focuses on discrepancies between models and observed behaviour, incorporating an individual's limitations and lived experiences.

Before continuing, the following key concepts are defined:

- **Subject**: An agent being observed for the purpose of analysis, in this case a social service client.
- **Observer**: An analyst or analysis tool observing the subject. Can also be represented a computational agent that is observing a subject agent.
- **Reasoning**: The process of making a decision based on inference, where "inferences either maintain or throw information away (deduction)[1] or they increase information (induction)" [122]. Also called "reasoning process."
- **Intuition**: The process of making a decision without reasoning [124]. Also called "intuitive process."
- **Behaviour**: Performed or planned actions and mannerisms in response to some stimuli [149, 24]. Can be based on reasoning and intuition.

2.2 Social Science Perspective

The social science perspective includes sociology and psychology fields. Each field performs similar analysis on human behaviour, and focuses on different levels of abstraction. Within social science, each level contains different schools of thought that interprets behaviour differently.

2.2.1 Sociology Perspective

Sociology is tasked with performing descriptive, diagnostic, and predictive analysis of social interaction, spanning the entire spectrum from micro to macro levels of abstraction. The focus of this thesis is the micro level, specifically the interaction between individuals and the social service system. According to sociology, an individual's decision making is influenced by a complex and dynamic social system and a shared symbolic representation of their society [141, 239, 234]. A logical consequence, then, is that the individual's society forms his or her beliefs, determines their means, forms preferences for goals, and creates a set of social norms with expected consequences of their actions [200, 47].

[1] Johnson-Laird and Khemlani [122] refer to deduction as "throwing information away," meaning observations can negate previously held beliefs and assumptions.

An individual's rational decision making in a social setting is based on rational choice theory and social exchange theory [273]. Sociology emphasizes the normative factors impacting negotiations between two or more agents, where each agent is maximizing its utility [75, 50]. Theories of rational and non-rational behaviour rely on an agent's cognitive limitations, heavily influenced by the work of sociologists Max Weber in the 1920s and Raymond Boudon in the 1980s [109, 274]. Weber attributes non-rational behaviour in rational agents to ingrained habits, intrinsic beliefs, social norms, and emotions.

While cultural and social norms are observable, the equally important role emotional factors play is a point of contention [141]. The work of economic psychologists Rik Pieters and Fred van Raaij (1987) identifies *functions of affect* in relation to objects in a subject's environment, namely the subject's organization, preferences, and maintenance of optimal levels of arousal in response to those objects [74]. Here, emotions have greater influence over decision making than in the cognitive system developed by Boudon and Weber. The work of sociologist Howard Becker (1945) and later social phenomenologist Alfred Shutz (1967) identifies this division as being between the subjective rationality of an emotional agent and the objective rationality of an observer [274]. More recent work in neurology has shown a close connection between emotional and cognitive activities in the brain [190, 15, 81]. This connection in the context of decision making will be discussed further in Section 2.2.4.

2.2.2 Psychology Perspective

Like sociology, psychology is tasked with performing descriptive, diagnostic, and prescriptive analysis, but focuses on an individual's behaviour rather than the society in which they are located. It focuses on understanding their behaviour and inferring their internal process from observable phenomena. The psychological perspective on non-rational behaviour is in line with that of sociology but focuses on the mechanisms of and causal factors for behaviour [109, 61, 12]. The notion of affect and rational reasoning with empirical information is grounded in specific situations and components involved, including memory, reasoning biases, and cognitive limitations [20, 243, 61].

Behaviourism, the psychological basis for understanding human behaviour, is based on observable stimuli-response (S-R) pairs [137]. Unobserved, hidden, or unknown relations are referred to as S-O-R where, "O" stands for the subject's internal "organism." The construction, systematic combining, and automated execution of such S-R relationships allows for the representation of a rational agent. However, the full range of required states and consequences of actions are not always known. In fact, all S-R relations but the most basic ones are not defined *a priori* for human agents. Instead, humans are conditioned, learning to adjust to situations through various interactions with their environment using their senses [223]. To an observer a subject's rationality does not exist as something remotely achievable. Rather, it acts as a reference point for degrees of behaviour orientation that may or may not follow a rational trajectory towards satisfying goals.

To fill the gap between the known and unknown factors, the subject's beliefs and emotional state play an important role along with biological, neurological, and social factors. The precise source of emotions within the brain is difficult to identify for three reasons. First, elicitors of emotions come from various parts of the brain [70]. Second, so-called basic emotions are not directly sensed by human beings [117]. What we sense is a combination of "basic emotions," with varying degrees or levels of valence [186]. Finally, the stimuli eliciting emotions is not consistent. There are many internal and external factors which affect how we interpret stimuli.

2.2.3 Social Science Perspective on Goals

For goal-driven agents, determining rationality should arguably start with evaluating goal preferences that play a role in guiding behaviour. Inferring goal preferences from observations is difficult since each goal generally requires several choices to be made, where each choice satisfies one or more subgoals. Goal-driven behaviour begins with motivation towards goals, but motivations are rarely incorporated in a tool. The difficulty of incorporating “motivation” into a tool stems from the lack of a concrete definition within social sciences and the inconsistencies between the vague definitions that do exist [134]. Nevertheless, “motivations” play a key role in goal-driven behaviour theories and architectures.

Rather than starting with assumed motivations of individuals to infer rational or irrational behaviour, we could begin by observing behaviour, then organizing goals into some intrinsic order. To satisfy goals, individuals develop and execute plans, monitor execution for errors, then modify and execute revised plans [114]. Simple goals do not require extensive planning, and the process from motivation to execution is relatively short. Complex goals require a temporal dimension as they need to be spread out over some period of time, broken up into multiple subgoals and actions that achieve each subgoal [241, 180].

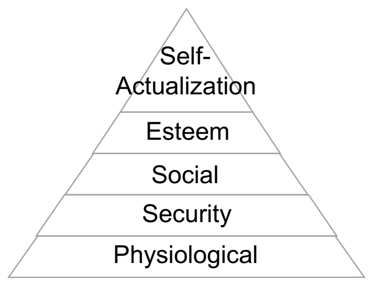


Figure 2.1: Maslow’s hierarchy of needs

While basic motivation is ill-defined, there is some consensus that behaviour models can rely on theories like Maslow’s hierarchy (MH) that grounds goals in basic human needs [160]. A need can be considered as a “master” goal that is an innate requirement for an agent and has no triggering activity, meaning they always exist with varying degrees of urgency. All other goals or subgoals are tangible propositions that can be achieved and satisfied through a series of activities. MH categorizes such tangible goal propositions into five categories of basic human needs. While there is mostly consensus on the categories, there is less consensus on the correct order of MH levels and whether it can be applied universally across populations and cultures [170, 128, 246, 111]. The first group of needs are short-term needs important to our survival. The second group are long-term needs that, put broadly, serve to improve our life and society at large.

The first need is physiological, a type of goal that ensures our body is in good general health to continue staying alive and functioning. These goals include sleeping, resting, replenishing our energy, and repairing our bodies. Security needs include goals that provide safety, such as a shelter, social order, stability, freedom from fear, and protection from various harmful environmental elements. Social needs include family, friendship, intimacy, trust and acceptance, as well as receiving and giving affection and love. The second group of needs are not necessarily required to stay alive and are more difficult to categorize as they usually span longer periods of time. Self-esteem is the need for personal achievement, mastery of a task, independence, social status, dominance, prestige, self-respect, and respect from others. At the top of the hierarchy is the need for self-actualization. It represents our motivation for reaching our full potential, accomplishing goals not essential to our survival but something which transcend our position as individuals in a society.

2.2.4 Social Science Perspective on Emotions

Emotions play a key role in the development of goals based on the perception of our environment [12]. They developed as a way to recognize resources that satisfy self-preservation goals and for developing social goals that elicit empathy and altruism in others [186]. However, the association of basic needs with emotional factors is difficult, and is often limited to transactional choices that ignore the time dimension of behaviour [70, 114, 45, 14, 217].

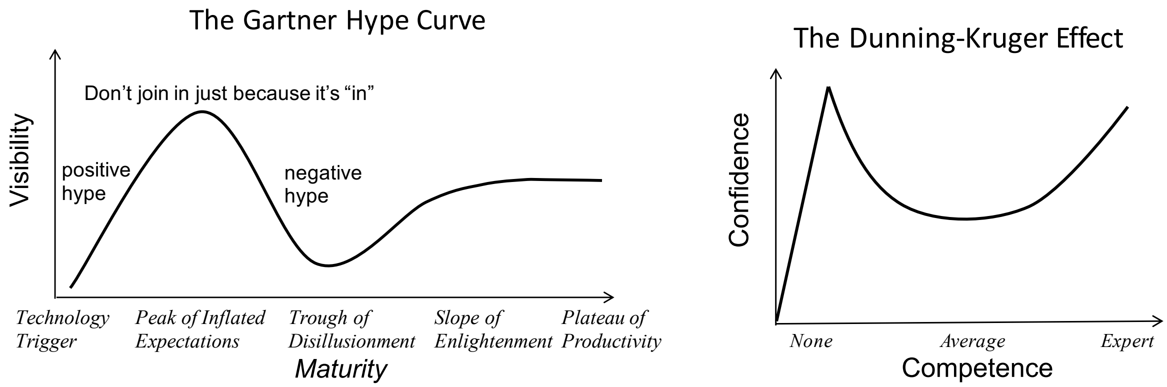
At a neural level, the underlying brain processes that seek stabilizing effects through accomplishing goals can be categorized into *cool* and *hot* emotion regulators [100, 275]. At a cognitive level, there are many theories of emotions that contribute to goal-driven behaviour. The vast majority, like BDI (belief-desire-intention) and OCC (Ortony, Clore, and Collins), rely on "drives" that form a direct connection between some stimuli and a response [203]. In this work, emotional states "trigger" appropriate actions based on the trigger's valence, a positive or negative emotional perception of the triggering event according to predetermined thresholds [96, 275].

Arnold and later Lazarus developed a cognitive theory of emotions called appraisal theory that captures how events are appraised before a response is triggered [220]. Arousal theory extends the notion of *cool* and *hot* emotion regulators with categories of emotions that regulate emotional arousal at a comfortable equilibrium [127]. The use of appraisal theory is often supplemented with the OCC model provides predetermined responses and valence for discrete emotions like fear, joy, and sadness [183].

The representations of emotions discussed so far are transactional and lack a time dimension. They rely on one-to-one associations between emotional characteristics of an agent's response to some event. Such associations are rarely observable in domains where experiments within a controlled environment are not possible, such as those that focus on homeless clients. An underlying emotional pattern that is revealed over time is a more suitable option for such domains. For example, when moving from destructive to constructive behaviour, a client transitions through multiple *stages of change* [174, 17, 157]. A practitioner must recognize these stages and guide the client accordingly.

The benefit of a time dimension is the normalization of a client's decision making process over an extended period of time, providing an objective external perspective. For example, how objective are homeless clients when self-assessing the likelihood of success in an intervention program? Often clients express unrealistic optimism about reaching goals without considering the steps to reach them [154]. Equally, clients can be overly pessimistic about reaching goals due to ongoing marginalization, despite being recognized as highly likely to succeed by external evaluators [244]. Recognizing that overcoming unrealistic optimism or pessimism takes time, it would be unreasonable to expect clients to make objective self-assessments about their progress in a program. Currently, no work exists that uses a utility function that captures movement between optimistic and pessimistic stages. Instead, models rely on well defined causal chains between events that lead to the emergence of and changes in emotional states [219].

Study of the phenomenon of moving between optimistic and pessimistic phases is not new, and has been applied at both macro and micro scales. At the macro scale, the "hype curve" introduced by Gartner research models the adoption rate of goods, services, or simply "ideas" in general [152], as depicted in Figure 2.2 (a). During the "positive hype" phase, some product may become popular among early adopters. Next, it is adopted by mainstream users and eventually peaks in popularity before falling



(a) The Gartner Hype Curve (b) The Dunning-Kruger Effect

Figure 2.2: Existing theories of optimistic and pessimistic cycles

into a "negative hype" phase where it drops in popularity. After some time, if the product's adoption is mature and production sustainable, its popularity among the population plateaus.

At the micro scale a similar pattern was observed for an individual's perception of their abilities by Justin Kruger and David Dunning in 1999 [66]. The Dunning-Kruger effect describes a phenomenon where individuals that perform poorly on a task are ignorant about their deficiency in skills, as depicted in Figure 2.2 (b). This deficiency causes them to make mistakes in performing assigned tasks. The individual is also unaware they are making mistakes unless they are prompted, a state referred to as meta-ignorance. Dunning evaluates performance and self-evaluation of poor and top performs, and the role that biases and bottom-up experiences have on the individuals. The concluding recommendation by Dunning and Kruger is that feedback does generally help in improving performance, but must be done in a way that does not discourage the individual from future attempts. Outstanding issues include individual differences in meta-ignorance, intelligence characteristics, and motivational characteristics.

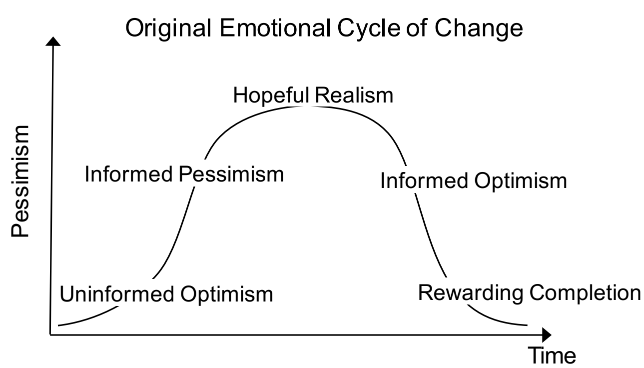


Figure 2.3: Original emotional cycle of change by Kelley and Connor [129]

The hype curve demonstrates how individual choices made by different types of consumer can be aggregated to recognizable patterns, while the Dunning-Kruger effect demonstrates how our own cognitive bounds prevent us from seeing our deficiencies and prevent us from objectively self-assessing our abilities. In addition to behaviour types and cognitive limitations, it is possible to identify patterns of optimism and pessimism by an individual's emotional mood. In one workshop[2] at a shelter for homeless clients, a modified version of the emotional cycle of change (ECOC) was used by a caseworker to assist clients with self-assessment. The workshop's objective was to help clients recognize emotional changes as they participate in various intervention programs by preventing uninformed self-assessment and encouraging informed reflection. The original ECOC was developed by Kelley and Connor as a function of pessimism over time, as per Figure 2.3 [129]. Here, an agent moves through five emotional stages as it perceive its circumstances as optimism and pessimistic. The agent begins in the "uniformed optimism" stage (UO) with low pessimism which gradually increases to high pessimism when the agent reaches the "hopeful realism"(HR) stage, then gradually decreasing back to low pessimism at the "rewarding completion" (RC) stage.

Based on knowledge that came from the "practice wisdom" of the caseworker running the previously mentioned workshop[3], a modified version of the ECOC was used that captures a client's mood and expectation of success over time as the client moves through optimistic and pessimistic stages, as per Figure 2.4. There are three modifications to the ECOC made by caseworkers during the workshop. First, the graph is a function of mood over time, with the direction of the function indicating expectation of success. A positive (upward) expectation of success indicates optimism while a negative (downward) expectation indicates pessimism. Second, a new stage, the "Valley of Despair" (VOD), is added that represents a state of the agent where it is "emotionally paralyzed" and cannot move forward to the HR stage without external help. The HR stage is reached only after the agent is given external assistance with enough optimism to exit the VOD stage. Without external help, the agent either remains in the VOD stage or cycles between the UO and the VOD stages. The third modification is the addition of a neutral mood for the agent where the function crosses the middle of the graph. Rather than starting in an optimistic state, the agent begins in a neutral state then quickly gains confidence and reaches the UO stage. When transitioning between the UO and informed pessimism (IP) stages the agent is again in a neutral state. Here the agent can decide whether to abandon its goals and pursue others or to continue, risking the VOD stage. Finally the agent is in a neutral stage when entering the "Success" (S) stage where it is confident about its ability to achieve its goals.

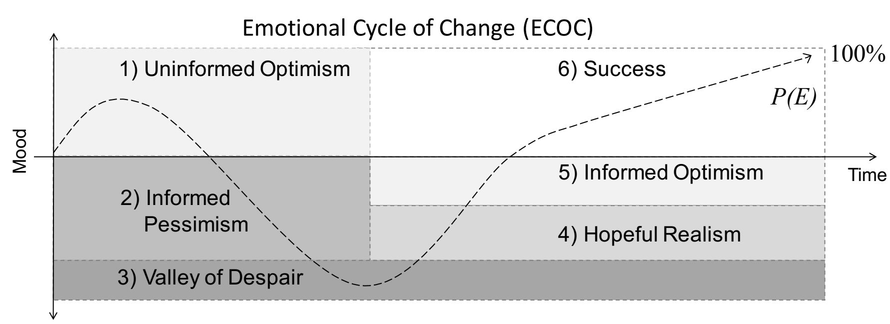


Figure 2.4: Emotional cycle of change showing a client's emotional "mood" regarding goals and "expectation" of success $P(E)$

The modifications better represented the emotional stages and moods homeless clients experience as

[2] I observed the use of a modified ECOC depicted in Figure 2.4 while working at a homeless shelter. Its use here reflects the applicability and utility of this technique in the field.

[3] "Practice wisdom" refers to the knowledge gained by social workers through their experience, which reinforces and expands their theoretical knowledge [213].

they interact with an intervention program. Compared to other theories of emotions, the time dimension makes ECOC suitable for dynamic environments like that of the homeless population [156, 121], where an understanding of individual beliefs, events, and emotional responses is not known but can be obtained through observations over time [143].

The ECOC graph in Figure 2.4 provides the type of nonlinearity required to capture human-centric progress towards goals. ECOC identifies stages where an agent may be pessimistic or optimistic while achieving its goals. Consider a practitioner evaluating the progress made by a client they are interviewing. If a client is overly optimistic about a goal they may be in the UO stage. Here the practitioner recognizes that unknown prerequisites and unforeseen consequences will prevent the client from achieving their goals. Once faced with this reality, a client may lose confidence and move into the IP stage. Without external help, they may succumb to hopelessness in the VOD stage. Given some help, the client may move into the HR stage. Continued improvements move the client through the Informed Optimism and eventually Success stages.

The ECOC has not been validated empirically in the homeless domain, but has been evaluated in other situations where people experience emotional changes in the dynamic environment, especially in the healthcare industry. The original ECOC devised by Kelley and Conor was presented as a way for practitioners to recognize their own stages of change as they handle the pressure of their duties [129]. Subsequent evaluations of ECOC focus on nurse practitioners as they adapt to changes in a dynamic environment of their daily work and interactions with patients [67, 143]. Mashazi evaluated ECOC as a way for nurses and patients to develop trust as the nurses (not the patients) deal with resistance to change [159].

2.3 Single Decision Making

Assuming we know how goals are ranked, how does an agent rank and select actions to satisfy its goals? Viewing each decision made by an individual in isolation allows us to evaluate behaviour objectively based on only those factors that impact a single choice and its consequences. A person's preferences and external constraints on that choice can also be evaluated independently from other choices. The most rational set of choices would then be those which include only the best individual choices. This is the perspective about rational decision making adopted by neoclassical economics. Decision theory provides the mechanism for reasoning about factors that influence decision making. As will be discussed in the following sections, bounded rationality and behaviour economics challenge many notions of neoclassical economics and decision theory.

2.3.1 Economic Perspective

The focus of economics is to perform *prescriptive* and *predictive* analysis of human interaction to identify changes that need to be made in order to find optimal means of achieving goals. With this in mind, economists view decision making as a series of independent choices, where every required choice is known and assigned a utility. Rational decision making then is choosing among a set of choices that maximize that utility, an ideal that, according to economics, only rational people exhibit.

Homo Economicus is a representation of humans as observing certain rules that can be described as rational, under a number of assumptions. Rationality in economics is based on the *rationality principle* "that individuals act in their best interest as they perceive it" [26, 79]. The theory also assumes that behaviour of individuals in a society translates to similar behaviour in their society as a whole. The notion of a utility function is introduced in order to measure and compare different means, with the optimal means having maximum utility due to the lowest cost or highest reward.

The economic understanding of a rational agent assumes that every factor required to recreate its decision is known. This includes the external conditions, constraints, and action outcomes, and finally the internal states of the agent, its goals, limitations, as well as how external and internal factors are perceived by the agent. The first formal operationalization of a rational agent's individual actions and outcomes was achieved by Herbert Simon and Allen Newell in 1971 with the "production system" [232]. It was based on the S-R relation introduced in Section 2.2.2. The production system is a set of "productions," relationships between conditions and actions. Conditions may include states internal and external to the agent, mimicking the "organic" portion of the S-O-R triple, while actions modify the state of the world [229].

Bounded Rationality

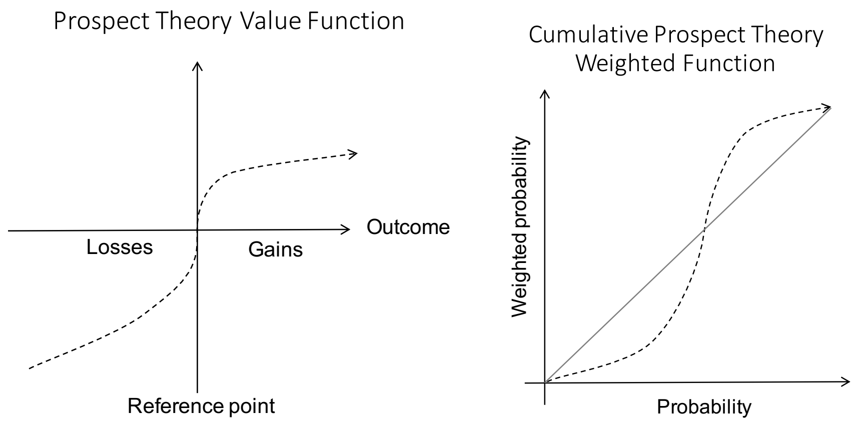
Following the observed limitations of work like the production system, and difficulty of capturing required data to reproduce actual human behaviour, Simon and Newell began to question the neoclassical notion of *Homo Economicus*. Such limitations and difficulties are especially true for activities with a high degree of risk or uncertainty [271]. Bounded rationality (BR), Simon's key innovation, provides a framework for incorporating cognitive and environmental constraints that may help interpret a client's seemingly "irrational" behaviour [226]. According to BR, there are three main types of bounds influencing an agent's decisions [226, 227, 228]. First, the information required to find an optimal solution is either incomplete or incorrect. Second, cognitive limitations prevent an agent from considering all possible factors, limiting them to only the most trivial problems. Third, we simply don't have enough computational time to evaluate all options required to solve a complex problem.

Within bounded rationality, individuals compensate for lack of information, cognitive limitations, or time by adopting different normative factors. Social norms and individual biases allow one to determine their actions based on the actions of others [75, 124, 274]. In extreme cases, for instance following past trauma, individuals develop coping strategies to help adapt to internal limitations and a dynamic external environment [55, 222, 163, 19, 53]. However, overcoming cognitive limits is not a linear process, and a number of studies have shown that it takes more cognitive resources and a more positive situation to overcome negative situations [4, 222]. Many models in economics have attempted to incorporate BR with varying degrees of success [208].

Behavioural Economics

Behavioural economics (BE) is a field within economics that attempts to address some of the shortcomings of the rational agent theory by categorizing different types of biases exhibited by individuals, incorporating sociology, psychology, and biology along with certain notions in economics [264, 29]. However, most theories based on BE have retained many of the basic principles of rational choice theory, and mostly extend them with cognitive limitations related to specific scenarios and biases found in economic literature [124]. The most applicable of BE theories, prospect theory (PT), was created by Kahneman and Tversky and is considered a descriptive model for decisions under risk [125, 252]. PT offers an empirically derived formulation of subjective utility and probability, and a more psychologically accurate theory than expected utility [166, 204, 150].

PT is based on a two-phase process that first edits provided information into a simplified representation, and second evaluates the simplified representation. The "editing" phase attempts to elevate any framing effects of the decision problem including acts, contingencies, and outcomes. The framing effect is a cognitive bias that causes humans to respond to potential gains as risk-averse decision makers, but to potential losses as risk-seeking decision makers. Framing takes into account the agent's norms, habits, and expectancies. Several methods are introduced for the editing phase, including coding the information into dominant frames, combining similar options into an aggregate form, and cancelling certain effects that are dominated by others.



(a) Value function successful outcome (b) Weighted probability function

Figure 2.5: Evaluation functions used by prospect theory and cumulative prospect theory

Next is the "evaluation" phase which assigns a utility to the choice and a weight to the probability of the choice's outcome. Here, the agent relies on a subjective value assignment for the outcome of each decision considered, based on the expected potential value function in Figure 2.5 (a). The weighted probability function adjusts probabilities approximately according to Figure 2.5 (b).

Two extensions to PT have been proposed that are relevant to this thesis. First, Tversky and Kahneman recognized some limitations of PT and created cumulative prospect theory (CPT) [253]. CPT simplifies the editing and evaluation phase to rely on simpler cumulative metrics for choices. The new weighting function, depicted in Figure 2.5 (b), treats probabilities as subjective cumulative probabilities. Unlike PT, CPT does not violate the stochastic dominance principle by considering an outcome better than another despite it having a lower probability of success. Also, CPT can be used to derive continuous outcomes, whereas PT can only produce discrete outcomes and small changes in the input can produce large differences in the utility [204]. To address these issues, Rieger and Wang created smooth prospect theory (SPT), which derives a probability distribution based on methods defined in the PT editing phase [204]. SPT can be considered a continuous model of PT which normalizes discrete factors normally removed by PT. Rather than selecting only the most dominant factors and combining similar factors together, SPT considers finite choices that could be made and calculates the probabilistic distribution of these choices. SPT has been successfully applied to agent models that simulate the stock market [57].

Despite its many strengths, PT and its extensions are not suitable to emulate homeless clients for a number of reasons. The editing phase requires a granular understanding of the factors impacting an agent's decisions. Such factors as norms, habits, and expectations are well defined for many economic problems and associated with different target populations. This is not the case with the homeless population, and generalization of such factors from the general population to the homeless population is not possible. Without the underlying factors, any normalization performed by either CPT or SPT would not reflect the unique and under-represented factors exhibited by people experiencing homelessness. It should be noted that for highly customized or controlled intervention programs it may be possible to obtain this level of detail (for customized programs) or enforce control measures (for controlled programs). This would make identifying and customizing such factors for each client possible. This approach would be well suited for intervention programs that impose a schedule on which services are delivered or conduct detailed in-person client evaluations. However, without required data, a self-directed program like Housing First is not well suited for such restrictions.

The second limitation of PT is its lack of a time dimension, making it suitable only for single decision making. The reference point used by the editing and evaluation phases for each decision is the agent's perception of the current situation. At first glance, the weighting function refined by CPT in Figure 2.5 (b) resembles the non-monotonic ECOC function. However, lacking a time dimension, CPT's weighting function is only used to change the perception of the choice's probability relative to this single reference point. The ECOC, however, explicitly defines how someone's perception of their situation changes over time.

SPT compensates for a lack of time dimension by representing the discrete outcome of PT as an outcome distribution which can be stochastically sampled. Agent-based simulations have been conducted using SPT for which agent decisions follow this distribution [57]. However, such a distribution is static, classifying the combination of agent simulation and SPT as a static simulation. Having a static simulation requires knowledge about factors used to build that distribution. A homeless person's environment, however, is dynamic and an observer cannot assume an agent will follow such a static distribution.

Despite its faults, many of which have been resolved by PT [253, 150, 204], expected utility has a much broader adoption in the AI community than PT or its extensions. While some systems have incorporated PT into simulation, these are applied to problems in the economic domains like stock markets [57] or under well-defined rules in game theory [272]. Bounded rationality has allowed many such systems to optimize around such limitations.

2.3.2 Decision Theory

Considering that the possible source of seemingly "irrational" behaviour are biases and bounds used to reason about goals and actions, how does one emulate behaviour with a rational reasoner? Assuming a rational agent is defined as one that maximizes utility, one approach may be to calculate the utility assigned to beliefs and preferences of the agent. Unfortunately, it may not always be possible to objectively and explicitly define the agent's utility assignment. It may be possible, however, to calculate beliefs and preferences from observed behaviour with the help of different theories of behaviour. *Decision theory* (DT) provides a mechanism for representing and calculating the utility of actions and goals.

There are two branches of decision theory that focus on different aspects of decision making [105]. Normative decision theory tells us how things should be, with an assumed understanding of the inner workings of the decision process. Descriptive decision theory tells us about how things actually are, with observed preferences that may be associated with specific decisions. With descriptive DT we must find a way to interpret the actions of others.

According to Bemrudez [25], decision theory must guide the observer's process for evaluating choices made by other people (the subjects), and predict or explain those choices. Several approaches have been used to systematically build an understanding of behaviour by an observer. Dewey proposed a multi-step sequential process, starting with defining the problem and possible solutions, making observations, collecting data, then accepting or rejecting the defined solutions [60]. Simon and Brim applied similar steps but in a different order, placing information gathering at the beginning rather than the end of the process. Critics of this work agreed with the individual steps needed, but argued that having a strict order was too restrictive for modelling the dynamic nature of human decision making [265, 105]. Whichever order is used, it is important that the observer is objective in their evaluation of the subject's behaviour.

2.3.3 Objective Decision Making

Objective decision making adopts Simon and Brim's approach to modelling behaviour by starting with observed choices, then calculating how individual choices are related. Table 2.1 defines required terms.

Table 2.1: Objective decision making terms

Term	**Description**
z_i	A choice available to the agent, indexed by i. A choice represents a lottery the agent can choose from amongst a set of lotteries. Each choice is made up of actions with different probability distributions of outcomes.
Z	Set of choices available to the agent, where $z_i \in Z$.
o_i	An outcome that is true following some choice z_i.
O	Set of outcomes, where $o_i \in O$.
p_i	Probability distribution over outcomes of choice z_i, where $p_i \in [0, 1]$.
P	Set of probability distributions, where $p_i \in P$.
$z_i \succ z_j$	Operator that weakly orders (see below) a set of choices where z_i is preferred to z_j.
$p_i \succ p_j$	The order operator can be extended to preference ordering over probability distributions associated with choices[4], where $z_i \succ z_j \implies p_i \succ p_j$.
a_i	Probability distribution over choices (i.e. lotteries), a_i, where $a_i \in [0, 1]$.
A^x	Sequence of choices, indexed by x.
A	All possible sequences of choices, where $A^x \in A$.
z_i^x	A choice z_i in sequence A^x, where $z_i^x \in A^x$.
o_i^x	An outcome o_i where choice z_i^x resulted in outcome o_i^x and $z_i^x \in A^x$.
O^x	The final outcome of sequence A^x.
$u(z_i)$	Subject utility assigned to choice z_i by some agent.
$EU(A^x)$	Utility assigned to the sequence A^x, as per Equation 2.2.

Expected Utility (EU)

Decision theory is based on the concept of preferences, an ordering of choices that dictates an agent prefers some choice z_i over some choice z_j in a set of choices Z, where Z is often referred to as a lottery. Expected utility (EU) theory provides a framework for calculating the order and preferences based on work developed by John von Neumann and Oskar Morgenstern in 1944 [258]. EU theory states that the $\succ$ operator *weakly orders* a set Z of choices whenever it satisfies the following four axioms.

[4]See Kreps, Chapter 1 for further discussion [139].

Axiom VNM-1 (Completeness: A preference is assigned to all pairs of choices.)

$$\forall z_i, z_j \in Z : z_i \geq z_j \vee z_j \geq z_i \tag{VNM-1}$$

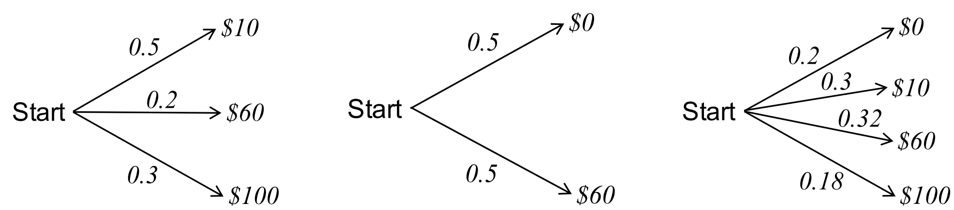
Axiom VNM-2 (Transitivity: Order of preferred choices is maintained across all choices.)

$$\forall z_i, z_j, z_k \in Z : z_i \geq z_j \wedge z_j \geq z_k \implies z_i \geq z_k \tag{VNM-2}$$

EU can represent ordinal (order-based) and cardinal (value-based) preferences by way of a utility function $u()$ [258, 268, 139]. An ordinal preference defines the preferred order of choices [191], as per Equation 2.1.

$$\forall z_i, z_j \in Z : u(z_i) \geq u(z_j) \iff z_i \geq z_j \tag{2.1}$$

Some problems also require a cardinal preference, the degree to which an agent prefers one choice over another, where that degree is based on some probability distribution over the outcomes[5] [139] . Consider two choices called lotteries, represented as chance nodes in Figure 2.6 (a) and (b). If a user chooses lottery 1, they have a chance of winning \$10 with probability 0.5, \$60 with probability 0.2, and \$100 with probability 0.3. If they choose lottery 2 they have a chance of winning \$0 with probability 0.5 and \$60 with probability 0.5. Such lotteries can be made up of any combination of games that have assigned probability distributions. For example, lottery 2 can be a coin toss with a fair coin that has 0.5 chance of heads with a reward of \$0 and 0.5 chance of tails with a reward of \$60. We assign p_1 and p_2 to the probabilities of lotteries 1 and 2, where $p_1, p_2 \in [0, 1]$.



(a) Lottery 1 (b) Lottery 2 (c) Compound lottery of lotteries 1 and 2

Figure 2.6: Chance nodes for lotteries, with probability distributions over those lotteries and their compound lottery

Next, there is a probability over the lotteries themselves that dictates which lottery is most likely to be chosen. We assign a_i to the probability distribution over lotteries, where $a_i \in [0, 1]$, and define a new compound probability distribution $a_i \times p_1 + (1 - a_i) \times p_2$. Here, if a_i is true lottery 1 is chosen, otherwise lottery 2 is chosen. Continuing the introductory example in Chapter 1 of Kreps [139], if lottery 1 has a probability 0.6 of being chosen, then lottery 2 has a probability of 0.4 of being chosen, where $a_i = 0.6$ and $(1 - a_i) = 0.4$. We then get the compound lottery $0.6 \times p_1 + 0.4 \times p_2$, giving the chance nodes in Figure 2.6 (c). Since $a_i > (1 - a_i)$, a user prefers[6] the probable outcome of lottery 1 (with distribution p_1) over the probable outcome of lottery 2 (with distribution p_2).

Finally, a user can have a preference over compound lotteries as well [139]. Consider a user that

[5] According to Axioms 1.1 to 1.5 in Kreps [139].
[6] According to Axiom 1.3 in Kreps [139].

can choose between three lotteries, each with a probability distribution of $p_i, p_j, p_k \in [0,1]$, where the user's pairwise preferences are $p_i \succ p_j \succ p_k$. The probability distributions over compound lotteries[7] are $a_m, a_n \in [0,1]$, where $a_m \times p_i + (1 - a_m) \times p_k \succ p_j \succ a_n \times p_i + (1 - a_n) \times p_k$. This implies[8] that $a_m > a_n$.

Von Neumann and Morgenstern recognized that combining choices with probabilities of successful outcomes becomes problematic when different combinations of choices can be compared. For this, they developed the notion of distance between choices based on the probability of successful outcomes, using an *interval-valued utility function* [258]. The axioms can be extended to a finite number of choices $z_i \in Z$ and outcomes $o_i \in O$, given that the probability distribution of each outcome $p_i : O \to [0,1]$ is such that $\Sigma_{p_i \in P} p_i = 1$ [139]. The bases for their argument lies in the *Archimedean* principle [139]:

> No matter how small $p_i > 0$ is and how big $p_j > 0$ is, there is an integer n such that $n \times p_i > p_j$.

This principle is captured for pairwise comparison of independent choices by von Neumann and Morgenstern as the *continuity* axiom[9] VNM-3 which states that, given choices z_i, z_j, z_k, and outcome preferences $p_i \succ p_j \succ p_k$, then there must exist probability distributions a_m and a_n such that

Axiom VNM-3 (Continuity: No outcome is so bad that it is not worth a gamble with a sufficiently high probability of success.)

$$\big(a_m \times p_i + (1 - a_m) \times p_k\big) \succ \big(p_j\big) \succ \big(a_n \times p_i + (1 - a_n) \times p_k\big). \tag{VNM-3}$$

According to Kreps this axiom states that [139] "there is no gamble p_i so good that for $p_j \succ p_k$, a small probability a_n of p_i and a large probability $1 - a_n$ of p_k is always better than p_j. Similarly, there is no gamble p_k so bad that for $p_i \succ p_j$, a large probability a_m of p_i and a small probability $1 - a_m$ of p_k is always worse than p_j." As Kreps points out, this requires that the choices one makes must be considered as a whole "package" rather than individual pairs of choices [139]. However, this is only the case if the probabilities of successful outcomes a_m and a_n are not equal to each other. This distinction leads to the *substitution* or *independence* axiom[10] VNM-4. It states that when two choices have the same probability a_m, evaluation of those choices is independent of our preference for the outcome. Given the choices z_i, z_j, and z_k, where $p_i \succ p_j$, then

Axiom VNM-4 (Independence: Preferences of compound choices are independent from the probability of those choices.)

$$\big(a_m \times p_i + (1 - a_m) \times p_k\big) \succ \big(a_m \times p_j + (1 - a_m) \times p_k\big). \tag{VNM-4}$$

Here, compound probabilities like p_i and p_k versus p_j and p_k are made up of individual choices z_i, z_j, and z_k. The compound probability $a_m \times p_i + (1 - a_m) \times p_k$ is preferred over $a_m \times p_j + (1 - a_m) \times p_k$ simply because $p_i \succ p_k$, regardless of how an agent feels about p_k.

Assuming the four axioms are true[11], combining the utility and probability of a choice we can now calculate the expected utility $EU()$ for a set of independent choices $z_i^x \in A^x$ with probability p_i^x in a sequence A^x [12], as per Equation 2.2.

[7] According to Axiom 1.4 in Kreps [139].

[8] According to Axiom 1.10 in Kreps [139].

[9] According to Axiom 5.3 in Kreps [139].

[10] According to Axiom 5.3 in Kreps [139].

[11] Allais' Paradox has showed that this assumption is not true [139]. The assumption is used, however, as a device for developing the argument in the thesis.

[12] Von Neumann and Morgenstern, and the economic literature refer to each choice z_i assigned a probability p_i as a "lottery," where the sum of all assigned probabilities equals 1, giving $\Sigma_{z_i^x \in A^x} p_i^x = 1$.

$$EU(A^x) = \Sigma_i u(z_i^x) \times p_i^x \tag{2.2}$$

$EU()$ makes it possible to qualify a set of choices as rational for any agent that maximizes $EU()$ given all possible sequences A^x and A^y in A. This is the approach[13] von Neumann and Morgenstern adopted to compare different sets of choices as defined by Equation 2.3.

$$A^x \geq A^y \iff EU(A^x) \geq EU(A^y) \tag{2.3}$$

2.3.4 Subjective Decision Making

Assuming an objective observer recognizes their own biases and bounds, we now discuss how they interpret the choices made by a subject being observed. We begin by assuming that the subject is an autonomous decision maker, from now on called an agent. We assume that from the observer's point of view, the agent's decisions are subjective, based on some desires and beliefs about the world. We also assume that the agent is bounded in its knowledge about the world. To understand subjective actions, decision theory relies on an extension to expected utility called subjective expected utility (SEU) for calculating an agent's beliefs about preferred goals and actions [221, 105]. Finally, we assume that the agent is rational and makes choices that maximize its own utility function, but is bounded in a way that impacts its choices. Table 2.2 adds new terms to those defined for objective decision theory in Table 2.1.

Table 2.2: Subjective decision making terms

Term	**Description**
S_t	State of the world, meaning what propositions are true at time t.
S	Set of possible states of the world, where $S_t \in S$.
s_i	Proposition with a truth assignment at some time t, where $s_i \in S_t$ means s_i is true in S_t at time t and false in S_t otherwise.
S_t^k	Subset of propositions true at time t, where $s_i \in S_t^k$ and $S_t^k \subseteq S_t$ then $s_i \in S_t$.
z_i	A choice available to the agent, indexed by i. Note that Jeffrey's theory (see page 25) treats choices as propositions, hence $z_i \in S_t$ if choice z_i was made at or before time t.
o_i	An outcome that is true following some choice z_i.
ϕ_i	Scenario is a proposition that an agent does not care about and has no control over but must consider before making its choices, where $\phi_i \in S_t^k$ and z_i is a choice dependent on ϕ_i being true.
p_i	Probability distribution over outcomes of choice z_i, where $p_i \in [0,1]$.
P	Set of probability distributions, where $p_i \in P$.
$A^x(S_t^k)$	Sequence of choices A^x applied to starting state S_t^k.
$s_i \oplus s_j$	Two mutually incompatible propositions, where either $s_i \in S_t$ or $s_j \in S_t$, but not both.
z_i^x	A choice z_i in sequence A^x, where $z_i^x \in A^x$.
o_i^x	An outcome o_i of a sequence A^x, where choice z_i^x resulted in outcome o_i^x and $z_i^x \in A^x$.
ϕ_i^x	A proposition ϕ_i on which some choice z_i^x is dependent.

[13] According to Theorem 5.4 and Equation 5.5 in Kreps [139].

Subjective Expected Utility (SEU)

A key limitation of EU is the assumed objectivity the agent exhibits when calculating the utility and probability assigned to a single choice. Consider the fact that the agent's desires and beliefs are impacted by the framing of the decision problem [251]. SEU theory, then, is concerned with preferences based strictly on the desires and beliefs of an agent. With SEU, the objective is not to determine whether an agent is maximizing its utility, but rather SEU is a method for the observer to identify and measure the agent's preferences and desires. Two main SEU theories are introduced and contrasted.

Savage's Theory for SEU

In 1954, Leonard Savage proposed a model of decision making as a process with scenarios and an outcome rather than simply as individual choices [216]. Outcomes o_i are redefined as propositions an agent cares about and has control over by making choices. Scenarios ϕ_j are defined as propositions that an agent has no control over. Scenarios are also the source of uncertainty in the decision making process due to the agent's limitation of seeing the entire state of its world and lacking control over scenarios being true or false.

For example, consider the situation of going for an enjoyable stroll outside. The choice z_i is whether the agent will "go for a stroll." The agent must consider several propositions (scenarios and outcomes) that may or may not be true about the world before and after making the choice. The scenario ϕ_j is "is raining" while the outcome o_i is "enjoyable stroll." The agent prefers the outcome to be "enjoyable stroll" but this is only possible if the scenario is false and it is not raining. According to Savage's theory, an agent's preferences for outcomes are objectively based on its beliefs about the probability of the outcome being a success. Utilities and probabilities are combined similarly to Equation 2.2. Suppose we have a set of propositions $s_i \in S_t$, a belief that the probability of outcome o_i occurring is $p(o_i)$, and a sequence of choices A^x, where a choice $z_i^x \in A^x$ has the outcome o_i^x. Then the sequence of choices A^x given an initial state S_t^k is $A^x(S_t)$, with a sequence utility of $U(A^x(S_t))$, as per Equation 2.4.

$$U(A^x(S_t)) = \sum_i u(z_i^x) \times p_i^x, \text{ where } S_t \text{ is the initial state.} \tag{2.4}$$

The comparison of different action sets applied to some set of states S can now be based on the comparison of their utilities, as per axiom 2.5. For all action sets A^x and A^y applied to state S_t,

$$A^x(S_t) \succ A^y(S_t) \iff U(A^x(S_t)) > U(A^y(S_t)) \tag{2.5}$$

Savage's theory requires six axioms to be true, prefixed with 'S'.

Axiom S-1. Ordering: The relation $\succ$ between two goal states is complete and transitive, combining axioms VNM-1 and VNM-2.

Axiom S-2. Sure Thing Principle: Choice preferences can be evaluated independently if the probability of one choice is not impacted by the outcome of another. This is an extension to independence axiom VNM-4.

Axiom S-3. State Neutrality: The preference of an outcome is independent of the current state, and has no impact on $U(A^x(S_t))$, a third extension of independence axiom VNM-4.

Axiom S-4. Preference of an outcome is independent of the outcome's utility, another extension of the independence axiom VNM-4.

Axiom S-5. A subject must not be indifferent to some sequences, and there must be some difference in utility between one sequence and another[14].

Axiom S-6. Non-Atomicity: If a sequence A^x is already preferred to sequence A^y, where $A^x \succ A^y$, then a new desired outcome proposition s_k added to outcome of A^y must have a sufficiently high probability p_k of success before $A^x \prec A^y$. If p_k is too low, sequence preference will not change.

Jeffrey's Theory of Subjective Expectation Utility

Richard Jeffrey's theory of subjective expectation utility introduced in 1965 is similar to Savage's, but makes two key contributions [119]. First, all probabilities are strictly based on Bayesianism, the updating of probabilities by conditioning on uncertain knowledge, and radical probabilism, that no facts are known for certain [118]. Second, everything that can be true or false in a particular world state is a proposition, there is no distinction between scenarios, outcomes, and choices. Since this also applies to choices, a predicate representing a choice is true if the choice was made and false if it was not. This allows an agent to consider multiple worlds when calculating the utility of a sequence of choices, multiple worlds being an important aspect of human behaviour [51]. Finally, each proposition is assigned a probability.

Jeffrey referred to utility as "desirability" and defined the utility function $Des(S_t^k)$, as per Equation 2.6. Here a desired state S_t^k has many partitions $S_t^p \subseteq S_t^k$, where S_t^p are sets of mutually incompatible but jointly exhaustive ways in which the S_t^k can be realized. Formally we have:

$$Des(S_t^k) = \sum_p Des(S_t^p) \times P(S_t^p \mid S_t^k) \tag{2.6}$$

where desirability of S_t^k is $Des(S_t^k)$, and $P(S_t^p \mid S_t^k)$ is the probability of S_t^p being true given that S_t^k is true. Consider a partition S_t^p made up of propositions where s_a means "is raining," s_b means "is sunny," s_c means "enjoyable stroll," and the choice s_d means "took stroll without umbrella." An agent can now calculate the desirability (utility) of taking an enjoyable stroll based on the probability of it raining and the agent taking an umbrella for the stroll.

The same conditions on the preference relation $\succ$ apply, namely completeness, transitivity, and continuity. It follows, however, that not all axioms in von Neumann's and Savages' theory apply. Due to Bayesian conditional probability, choices are not strictly independent, contradicting axioms VNM-4 and S-4.

Jeffrey's theory introduced two new axioms, prefixed with 'J'.

Axiom J-1. Averaging: For some preference ordering $\succ$, if propositions s_i and s_j are mutually incompatible then choosing one or the other has no impact on the overall preferences, where:

$$s_i \succ s_j \iff s_i \succ (s_i \oplus s_j) \succ s_j. \tag{J-1}$$

Axiom J-2. Impartiality: Given two sequences of choice propositions A^x and A^y, if $U(A^x) = U(A^y)$ and they are mutually incompatible, then a new choice z_i changes $U(A^x)$ and $U(A^y)$ in

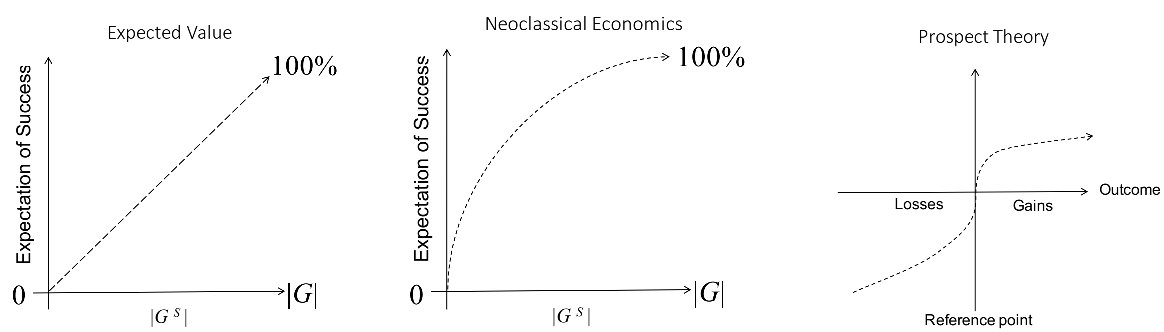
[14] This is considered a structural axiom to ensure the subject can be recognized as a rational utility maximizer.

the same way, where:

$$U(A^x) = U(A^y) \implies U(A^x \vee z_i) = U(A^y \vee z_i). \tag{J-2}$$

Calculating Subjective Expected Utility

Subjective expected utility provides a theory for comparing sequences of actions based on the utility and probability of each choice in the sequence. The manner in which utilities and probabilities are calculated is application specific. The most common application of SEU involves economic decisions, focusing on an agent's expectation of success or ability to handle risk. Multiple theories have been devised to calculate SEU. As a baseline, we begin with a simple version of expected utility function that does not rely on any prior information, only what can be observed at a particular moment. Figure 2.7 (a) demonstrates such a utility function calculated by taking the ratio of satisfied goals ($|G^S|$) relative to all goals ($|G|$). The second function, in Figure 2.7 (b), is based on neoclassical economic theory that presumes diminishing returns over time [260]. Finally, in Kahneman and Tversky's Prospect Theory (as discussed in Section 2.3.1) attempts to calculate the expected utility of biased decisions [125]. Prospect theory offers an empirically derived formulation of subjective utility and probability, and a more psychologically accurate theory than expected utility [166, 204, 150]. Here, biased decisions are treated differently when an agent is choosing between gains and losses, as per Figure 2.7 (c).



(a) Expectation of success based on $\frac{|G^S|}{|G|}$

(b) Expectation of success based on neoclassical economics

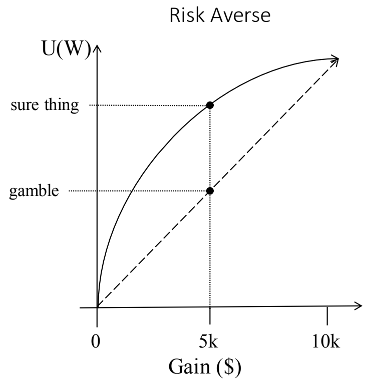
(c) Expectation of success based on prospect theory

Figure 2.7: Different metrics for expectation of success

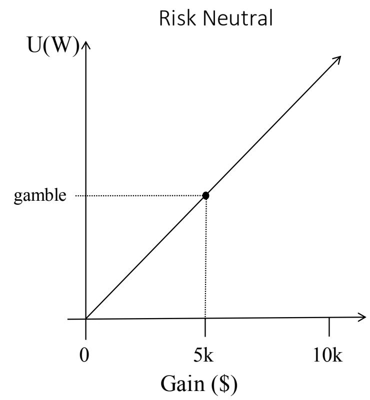
Other theories qualify the agent's approach to risk rather than calculating the utility from choices it makes [251, 270]. Such risk-based expectation functions rely on describing an agent as, for example, risk averse, risk neutral, or risk seeking, as per Figures 2.8 (a) to (c).

2.3.5 Human-Centric Single Decision Making

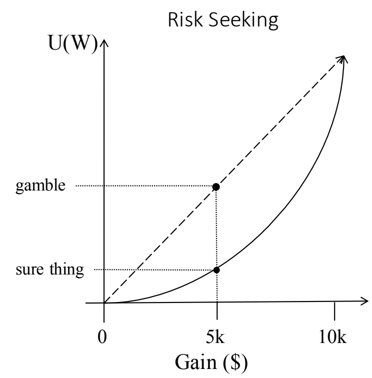
Single decisions consider information available to the agent, beliefs, current desires, and an evaluation of the current state of the world. Without a time dimension, the agent is only bounded by its available information. For example, reducing hunger is a goal that the agent knows about, and a known action may be buying food at a store. An agent may be missing information about alternative actions to reduce hunger, such as visiting a food bank. Information may also be missing about goals themselves.



(a) Expectation of success based on risk averse utility U(W)



(b) Expectation of success based on risk neutral utility U(W)



(c) Expectation of success based on risk seeking utility U(W)

Figure 2.8: Different metrics for expectation of success

For example, a common coping strategy for handling stress is overeating [158, 155, 10]. The immediate satisfaction of consuming food does not relieve the unrealized goal of reducing anxiety.

Maslow's hierarchy grounds an agent's goals in basic human needs. A single decision can be made for short-term goals mapped to lower MH levels, such as reducing hunger or finding a secure place to stay. Long-term goals at higher MH levels are more difficult to represent as single decisions as they generally involve multiple steps or do not require an immediate decision. We must also consider the fact that only abstract representations of actions can achieve basic MH needs since concrete goals generally require multiple steps. For example, eating food satisfies the physiological abstract MH need for replenishing nutrients, but requires multiple subgoals such as having a job, having money, buying food, and so on.

The calculation of a utility requires that goals, subgoals, and actions be provided *a priori*. Each action's outcome becomes a subgoal towards satisfying an abstract MH need. Conditional goal mapping may also change the underlying need that is being satisfied. For example, the goal of owning a phone can be mapped to either a security or a social need depending on the agent's age. For elderly homeless clients, having access to a phone is a security need that is required to ensure safety in times of emergencies. For non-elderly homeless clients, a phone satisfies the social need to connect with friends and family.

Emotions also contribute to the calculation of a decision's utility. First, a past event has an effect on the agent's emotional state. Second, the probability of an action is calculated based on the resulting emotional state. However, the evaluation may not calculate utilities in an objective manner. For example, emotional eating is a coping mechanism for reducing stress [235, 148]. An emotional valence associated with food is used to regulate emotional mood whether the mood is associated with food or not. Individual foods may also be associated with a positive or negative valence independent of their actual effect on the agent. Similarly to the OCC theory of emotions introduced in Section 2.2.4, the valence of needs must be mapped to appropriate food and mood pairs *a priori*.

2.3.6 AI Perspective on Human0-Centric Decision Making

The objective of artificial intelligence (AI) algorithms is to create reasoning mechanisms that equal or exceed human performance. Many methods have focused on making algorithms more efficient in finding optimal solutions, and some need to scale to a large number of human-like agents [137, 69, 238]. These approaches have focused on removing human-like errors and biases, while mimicking human-like decision making with respect to social and structural factors. As with economics, the underlying reasoning process or belief system is assumed to be sufficiently understood to be implemented and tested.

The belief-desire-intention model (BDI) [34] is well suited for representing the reasoning of a human agent as it explicitly defines an agent's goals (desires), available actions (intentions), and rating mechanisms for associations between goals and actions (beliefs). BDI architectures rely on modal logics for defining some level of commitment that rational decision makers must make towards their decisions [203].

Multi-agent simulations (MAS) provide the opportunity to try different "what-if" scenarios under different agent decisions and environmental constraints. Rational agent theory, and economics in general, is committed to methodological individualism which claims that all social phenomena are only explainable through individual actions and motivations [26]. Hence, single decisions executed in an iterative fashion can simulate social behaviours as well [90]. With MAS, a system is modelled as a set of autonomous agents that interact with each other and their environment [30, 54]. Each agent has unique skills and constraints, and can exhibit independent behaviour based on the economic model of a rational agent [26]. Agent simulation systems like Repast are based on the BDI architecture that focuses specifically on decisions that result from social interactions [177]. Some systems, such as "emotion, feeling, temperament," or EFT, incorporate OCC to model those interactions [116].

Cognitive architectures (CAs) attempt to mimic human components of decision making, such as memory, cognitive abilities, and biases. CAs like ACT-R [6, 5], Prodigy [41], ICARUS [144], and Soar [142] provide the architectural foundation for representing agent states using memory modules that can be made artificially impaired [146, 59, 179].

Probabilistic models are used when assumptions about agent beliefs can be made. A Bayesian network is a probabilistic directed acyclic graph[15] that represents dependencies between two or more events. Given a network, Bayesian inference can be applied to the interpretation of human behaviour if the probability of observed behaviour can be associated with an event [193, 256]. Stochastic dynamic programming (SDP) has been evaluated to explain choices individuals make by contrasting observed choices with optimal ones [189]. This approach can be used to derive an optimal policy that identifies choices that should be made to maximize some utility function. Markov decision processes (MDP) provide a framework for modelling optimal stochastic decisions for optimizing human workflows and interactions with controllable systems like robots [73, 162]. Markov decision process can be used if 1) the Markov property applies: the conditional probability distribution of future states depends only on the current state, 2) the joint probability distribution of future states does not change over time, and 3) individual choices are based on probabilistic distributions and incurred costs or rewards of an action.

Arousal and appraisal theories of emotions (see Section 2.2.4) have been implemented by AI systems in different ways. The vast majority of systems associate emotional appraisal with events using explicit rules [151]. These include CAs like ALEC and MAMID. Systems like GMU, BICA, and FAtiMA supplement appraisal theory with OCC models to provide predetermined responses to events with discrete emotions like fear, joy, and sadness [214, 63]. Valence can be assigned to emotions, with positive emotions linked to more important goals. CAs that use appraisal theory with OCC include Soar-Emote and H-CogAff [151]. In arousal theory, weighted drives towards some action control emotional responses to events. CAs

[15] In a probabilistic directed acyclic graph, each edge between two nodes has an assigned probability and direction, and the graph has no cycles [187].

that utilize arousal include a number of ACT-R extensions by Belkin et al., Fum et al., and Cochran et al. [151], as well as work by Ahm that also incorporates prospect theory [3].

2.4 Sequential Decision Making

Whether an agent is rational or irrational, decisions are never made in isolation. A goal utility and action probability should not be calculated in isolation either. In single decision making, preferences and information that influence a decision are limited to those available when the decision is being made. Many unknown or unobservable factors, such as an agent's preferred goals, emotional state, available information, or other limitations, are predetermined and remain static. This has ensured that expected utility axioms of completeness, continuity, transitivity, and independence are satisfied. The resulting agent behaviour is then based on independent choices made in isolation from each other. In the real world, however, such unknown factors are not static but dynamic, changing from one moment to another.

2.4.1 Sequential Decision Theory

Human behaviour is a series of choices over time, and the temporal dimension must be considered when calculating expected utility based on changing preference for goals and selected actions. When attempting to interpret a subject's decisions over time, an observer may take a naive approach, searching through all possible variations of a subject's options. However, such a process would continue indefinitely, rendering it impractical for all but the simplest behaviour. Some functional bounds must be applied.

First, similarly to single DT, the world in which the subject exists is limited to known states, hence the information bound applies to sequential DT as well. By adding the time dimension, the agent is also bounded by the length and complexity of the sequence of actions, hence the time and cognitive bounds apply as well. Each bound can be interpreted in a number of ways, discussed in this chapter.

Sequential decision theory is not concerned with comparing individual choices, but complete sequences of choices. Sequential DT calculates the utility of all observed choices before calculating a final sequence score using some variation of Equations 2.4 for $U(A^x)$ or 2.6 for $Des(S_t^k)$. Sequential DT also relies on observations of a series of choices combined to understand the agent's desires and beliefs. Given a sequence, it is important to understand why an agent, given the same scenarios, may make different choices. Relying on a series of choice to interpret behaviour introduces the notion of a *dynamic choice theory* (DCT) and decision strategies employed by an agent [25, 104].

Dynamic Choice Theory

Dynamic choice theory (DCT) represents an agent's decision making as a "strategy" that spans multiple choices over time where decisions may change at each time point. An agent can form preferences over such strategies. Hammond has identified three such strategies that focus on the agent's approach to calculating utility of decisions over time, namely *myopic*, *sophisticated*, and *resolute* [104, 161]. The *myopic* or naive strategy is based on single DT where the choice of an action is based on the utility of immediate actions at the current time. The *sophisticated* strategy considers the utility of all sequences starting from the current time, and chooses the sequence with the highest expected utility or lowest risk, recalculated at each new step. Finally, the *resolute* strategy also calculates the utility of all sequences but only at the beginning of the decision process. Once a sequence is selected it is followed until the end. This strategy is considered the most resilient to change of the three.

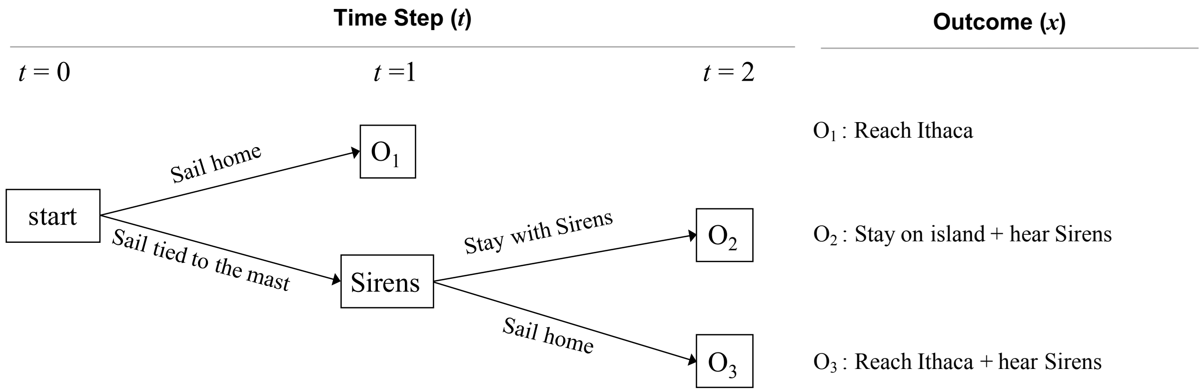


Figure 2.9: Ulysses' decision problem

To demonstrate each strategy, consider the famous Ulysses decision problem represented as a decision tree in Figure 2.9 [25]. The Ulysses decision problem describes Ulysses' journey home from Troy to Ithaca with three possible outcomes. Ulysses has the choice of sailing past an island with singing Sirens or sailing straight to Ithaca. While he prefers to sail pass the Sirens to hear them sing, he knows once there he may be tempted to stay with them on the island (or wreck the boat as some versions tell it), never reaching Ithaca. Ulysses must make a choice at the start of his journey whether to sail home, avoiding the sirens, or be tied to the mast and sail past the sirens and hear them sing, without staying on the island (or wracking). Sailing straight home guarantees not sailing past the Sirens and reaching Ithaca (outcome O^1). Choosing to sail tied to the mast, Ulysses plans to sail past the Sirens to hear their singing. Once there, he has a choice of persuading his crew to let him go to the island and stay there (outcome O^2) or trusting his men to keep him tied to the mast and continue towards Ithaca (outcome O^3).

Figure 2.9 illustrates the way preferences can change at different points in time, breaking the transitivity axiom. At the start time $t = 0$, Ulysses' preferences are $O^3 > O^1 > O^2$, while at $t = 1$ they are $O^2 > O^3 > O^1$. Since at $t = 1$ outcome O^1 is not in the decision tree at all, we can say that it's utility is zero. Following the *myopic* strategy, at time step $t = 0$ Ulysses prefers O^3 and sails tied to the mast towards the Sirens, believing it is the choice that produces maximum utility. At time $t = 1$, however, Ulysses' plan changes when he prefers to stay on the island and wants to persuade his sailors to let him go, never reaching Ithaca, as per outcome O^2. Relying on the *sophisticated* strategy, Ulysses determines that outcome O^1 has the least risk of being lured by the Sirens and to sail directly home to Ithaca. Finally, following the *resolute* strategy Ulysses considers all outcomes at time step $t = 0$, but this time commits to his original goal to achieve outcome O^3 and trusts his sailors to prevent him from staying on the island at time step $t = 1$.

Using these strategies, we can categorize an agent not simply by its individual choices but by the strategy it uses to calculate the utility of a sequence. Table 2.3 shows how Ulysses ranks eventual outcomes at each time interval, $t = 0$ and $t = 1$, depending on his strategy [25].

The myopic strategy, that ultimately results in outcome O^2, considers O^2 as the third best outcome at time step $t = 0$. It is not until time $t = 1$ that O^2 becomes Ulysses' first choice. The resolute strategy does prefer its outcome O^3 over others, and it's easy to understand why the choice to sail tied to the mast and trust his sailors was made at $t = 0$. At time $t = 1$ Ulysses must resist the urge to stay on

Table 2.3: Ulysses' dynamic choice strategies

Strategy	**Outcome**	$t = 0$	$t = 1$
myopic	O^2	3rd	1st
sophisticated	O^1	2nd	3rd
resolute	O^3	1st	2nd

the island, since O^3 is now rated as second over O^2. It seems that at $t = 0$, a myopic Ulysses believes he is using the resolute strategy, and can resist the Siren's singing. In fact, it would be difficult to differentiate myopic and resolute strategies by the single choice at $t = 0$ alone. Not until $t = 1$ would it be made obvious which outcomes Ulysses truly prefers, and which strategy he was using. Finally, the sophisticated strategy seems to go against Ulysses' preferences at each time point, since outcome O^1 is not ranked first at $t = 0$ or $t = 1$. The sophisticated strategy could be characterized as risk averse, focusing more on reaching Ithaca and avoiding the risk of staying on the island.

2.4.2 Dynamic Choice Theory and AI Planning

DCT alone assumes only reasonable choices are made at each point in time, given known factors and the true state of the world. What is considered reasonable, however, is subjective. Consider a situation where Ulysses decided to go back to Troy after arriving on the island. Or perhaps Ulysses cancels the trip to Ithaca completely and stays at Troy. What utility would be calculated for these perhaps unlikely but nevertheless possible choices? If they are deemed to be irrational, they would score a low utility, but considering them allows for an observer to assign a utility to such unexpected choices.

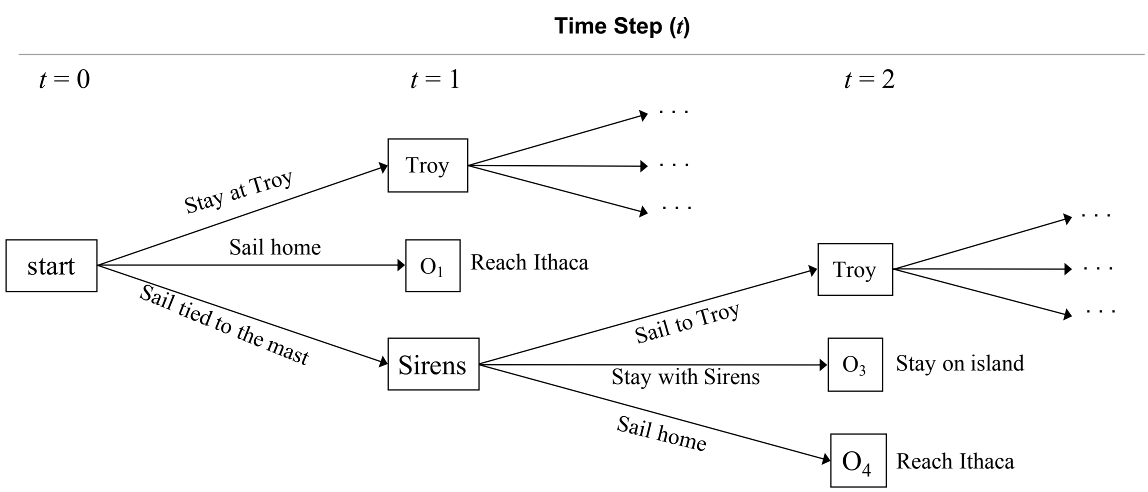


Figure 2.10: Ulysses' decision problem as a search tree

AI planning provides a framework for generating all combinations of objectively possible options for evaluation. We begin by defining a "planning problem" that consists of the initial state of the world and the goal states that need to be true at a future time. Then, given all possible actions, a plan is created by generating a structure called a search tree with all possible actions (edges) that transition between states (nodes). An algorithm then searches through plans in the tree and selects the "best" one. Unlike a decision tree, which contains likely decisions made by an agent that lead to observed outcome states, a search tree contains all reachable states whether an agent would reasonably choose them or not. The tree begins with the initial state node. An algorithm generates all possible paths of actions that transition the initial state to a state where goals are true. Each action has prerequisite propositions that need to be true before the action is executed. An action is inserted into a path if it is executable given the state of the world. The outcome state of each action now becomes the new state of the world. All available actions are defined in an action schema known by the agent.

An AI planning algorithm creates a search tree of all states that are reachable given different sequences of actions that can be performed, provided that prerequisites are true before each action, as in Figure 2.10. Most planners have some mechanisms to avoid creating branches arbitrarily. For example, one of the first goal-driven planners, STRIPS (STanford Research Institute Problem Solver), selects an action that satisfies an outstanding goal state, and generates a path to resolve that action's prerequisites [83]. Once actions in the new path are completed, the original action could then be executed to satisfy the original outstanding goal state. For example, sailing from Troy directly to Ithaca is only possible if Ulysses is tied to the mast.

2.4.3 AI Planning, Replanning, and Bounded Rationality

Like single decision theory, sequential decision theories such as DCT are bounded by information ($BR(I)$) being incorrect or missing. Sequential decision theories are also dependent on the time dimension which impacts the remaining two bounds, time and cognition. The time bound ($BR(T)$) limits the time a reasoner can spend iterating through all possible combinations of actions in the generated search tree. The cognitive bound ($BR(C)$) limits the complexity of plans that can be considered. Both time and cognition are open to interpretation by designers of the planning algorithm to suit their needs. For example, rather than being viewed as inherent limitations of any agent, most planners perceive bounds as obstacles, and devise various methods for overcoming them. Such methods, as described below, use approximations of the real world, like minimizing computation time through streamlining processes, efficient use of internal memory storage, or methods for substituting missing data. An error is then calculated as the difference between planned states and actual states after execution in the real world. This general error-reduction approach to plan improvement has not changed since its original conception as part of the General Problem Solving program (GPS) in 1959 by Newell, Shaw, and Simon [172].

Since GPS, various plan representations and techniques for efficiently reducing errors have been proposed. Monitoring reduces the cognitive requirements needed to generate complete solutions to a problem, relying instead on catching errors during execution and replanning. While missing from the original STRIPS planner, many of its extensions have incorporated such functionality [83]. Prodigy is a total-order backwards chaining planner that continuously builds a plan while monitoring plan execution and the state of the agent [84]. To overcome time limitations, planners like NOAH, NONLIN, SIPE, PRS, and PRIAR can execute and monitor multiple operations in parallel [210, 242, 262, 93, 126]. Anticipatory classifier systems are a group of classifiers that rely on reinforcement learning to monitor and improve performance of created plans [238].

Managing information with modular memory storage allows for more flexibility during the planning process. An opportunistic planner distributes planning decisions to "specialist" modules that can independently view plans at different levels of abstraction, monitor execution, and perform replanning [108]. The procedural reasoning system (PRS) uses the BDI paradigm to organize and manage information as beliefs, desires, and intentions [93]. A lack of abstract representation in STRIPS prevents it from making better use of limited internal memory. STRIPS+PLANEX+MACROP is an extension of STRIPS with the ability to learn "chunks" of information recalled together to reduce the complexity of a problem [82]. ABSTRIPS is an extension of STRIPS that uses a hierarchical representation of states to generalize and specialize information at appropriate points in the planning process [209].

More recently, planning systems have incorporated methods for overcoming human-like bounds and improving reaction time during execution, as reviewed by Hendler et al. [110]. The PUG/X system explicitly sets cognitive bounds on the search tree, as well as the number of plans to consider, before stopping search [145]. There has also been some research on reproducing cognitive impairments that cause bounded reasoning. For example, Nuxoll et al. evaluated Soar's episodic memory to investigate how well it performs with different types of memory [179]. Benton et al. focus on identifying and planning for a subset of most important goals, a method referred to as *partial satisfaction planning* [23]. This approach can be contrasted with systems that retain goals but modify or repair existing plans, as in the case-based planning literature. Lee et al. propose a hierarchical case-based reasoner that selected parts of previous plans to modify the current plan [147]. Hierarchical goal networks similarly repair plans with predefined methods [225]. Rizzo et al. extend the Prodigy planning architecture to include abstract goals and reactive action packages for execution [206].

Other related systems rely on goal reasoning to control plan regeneration rather than refinement. Cushing et al. provide a framework for satisfying abstract goals defined as commitments (required objectives) and opportunities (optional objectives) [52]. Replanning selects objectives for goals that must be satisfied to maximize utility and minimize cost. PUG/X triggers replanning when one of four anomaly types are detected during execution, at which point it generates new plans given the current state and goal rankings [145]. Some systems like PrefPlan and AltAlt^{PS} rely on predefined common-sense rules that decide when to modify a plan and reprioritize goals [33, 255].

2.4.4 AI Perspective on Needs and Emotions

Goal-driven behaviour has been explored by many AI systems, especially by AI planners. A set of plans are generated and evaluated by the agent using some quantitative metric, before the agent selects a plan considered to be the "best" one. That metric can be based on subjective beliefs about actions and objective utility of goals. The selected plan then acts as a trajectory of an agent's behaviour.

As discussed in Section 2.3.5, outside of predefined goals and static emotional responses, AI planning has not traditionally focused on representing the multitude of dynamic factors influencing human behaviour. Instead, the focus has been on overcoming the shortcomings of human reasoning by creating a number of representation models that improve efficiency and by the development of various optimization techniques. Many AI systems simulate human tasks at different cognitive levels, organizing goals and calculating utility in order to make such simulation possible. These methods are well suited for emulating high-level tasks, including scheduling and planning, with applications in various fields from robotics to industrial engineering [211]. For example, they are able to construct large search trees with many possible combinations of actions, pruning the tree only when required.

As a baseline, consider a typical application of AI agents: the planetary exploration rover. A teleological rover will have various predefined goals, such as performing certain experiments and capturing photographs, and a number of actions it relies on to satisfy those goals. Such goals are referred to as *achievement goals*, characterized by being proactive in nature and generally embodying why an artificial intelligent agent was created in the first place. To support its achievement goals, certain goals must be continuously maintained, such as power levels, selection of "interesting" rocks, and adapting to certain terrain obstacles while in motion towards those areas. These are referred to as *maintenance goals* or subgoals, characterized by being reactive in nature, triggered only when certain conditions are met. Based on the state of the rover, its computer generates and searches through plans to satisfy its achievement goals and maintenance subgoals.

While efficient, this approach is not representative of the process humans use to identify goals and satisfy them. The way humans perceive, rank, and respond to goals is much more dynamic. A number of architectures implement complex reasoning about goals, through perception, ranking, and clustering that attempt to mimic human processes [175, 214, 36]. However, like the rover example, in most architectures, goals do not emerge naturally, but rather fixed subgoals are added to an existing plan using predetermined and optimized instructions.

The most substantial work related to the ranking of needs is explored in the goal reasoning literature. Meneguzzi et al. propose a hierarchical representation of goals expressed as commitments [164]. ICARUS uses hierarchical goal definitions and a reactive goal management process, with later versions reprioritizing goals as the agent's situation changes [144, 44]. Shivashankar et al. introduced the hierarchical goal network, a set of predefined methods that define the relations among operators, goals, preconditions, and subgoals [225]. ActorSim is a simulator and planner with goal refinement capabilities [207]. It uses hierarchical goal and task networks from which the agent learns to perform sophisticated tasks efficiently.

As with goals, human-centric AI planners require emotional responses to be provided *a priori*. Most systems rely on predefined associations between an emotional appraisal and specific events that use explicit rules [151]. Ojha et al. propose a replicable, domain-independent computational model for emotional plan appraisal that generalizes the assignment of emotions to events [182]. Such generalization, however, contrasts with most emotion-based planners, like ACRES/WILL, ActAddAct and EM-ONE that rely on predefined associations between emotional appraisals of specific events, as Lin et al. [151] discuss. Lin also contrasts how systems like FAtiMA, EM, FLAME, Émile, and work by Gmytrasiewicz et al. [62, 202, 71, 97, 94] rely on appraisal theory and the OCC model [183]. OCC provides a framework for reasoning about emotional factors that control human decisions. It is used by AI planners to associate events with discrete emotional responses and valence, *a priori*. AI planners like EMA utilize arousal theory and weighted drives to rate the utility of plans [96]. Emotions have also been used as replanning triggers. For example, Steunebrink et al. [237] propose a hierarchical representation of emotions that statically links objects, agents, and consequences of events.

2.5 Homeless Client Emulation

Models for emulating client behaviour have a long history of success in the social services field. In the 1970s it was argued that due to technological limitations it was unrealistic to emulate a client's decision making process correctly [65]. Client models were limited to a small number of aggregate characteristics that could be obtained objectively by professionals appraising client actions and needs. Focus was instead placed on detailed metrics and models that evaluated the professionals and service delivery systems, leading to the majority of operations research (OR) work in healthcare today.

Since the 1980s, advancements in modelling techniques have allowed practitioners to focus more on the needs, constraints, and spending patterns of social service clients [64, 267]. Researchers have studied the impact a client's environment has on their needs, how they acquire resources, learn about new services from their peers, and align their preferences for services based on their peers' experiences. This work categorizes clients along multiple dimensions, focusing on needs, constraints, and decision making for different client demographics. A new picture of social service clients began to emerge that moved away from common negative stereotypes. The increase in information led to higher fidelity models that incorporated the impact constrained resources and conflicting needs have on the lives of clients. The collected information set the groundwork for models in use today [28].

Since the 1990s client emulation has been used to educate and evaluate students in the social services through experiential learning. Originally, human actors were used to emulate client behaviour with high fidelity, before lower fidelity computerized clients were introduced [192, 153, 266]. By identifying the crucial characteristics that influence client behaviour, educators can focus in on specific training scenarios customized for each student's educational objectives. Through role playing, a student can not only practice learned skills but also become aware of any emotions and biases they may have towards a client, something not possible through written tests. Simulation has also been used to study the impact of social service policies by simulating choices service providers make [236, 185, 106]. By relying on low-fidelity models, focus was placed on how those choices influence the behaviour of targeted clients with a limited scope of reasoning abilities.

2.5.1 Role Playing and Role Reversal

Experiential learning offers participants the ability to engage with a subject in an interactive and effective way under standardized evaluation criteria [169, 27].

In one example, a special workshop (WS) was organized to help 11- to 15-year-old students understand and relate to the experiences of fellow students who experienced homelessness or were refugees [56]. The workshop consisted of presenting a play with a follow-up discussion. It encouraged students to take an active role in their society by developing good relations and respecting different members of society. Such programs have been extended to other projects promoting experiential learning that involves direct interactions with homeless clients [169].

Another simulation initiative targeted at the community is the "Make The Month" (MTM)[16] project, which challenges its participants to survive a month on the resources available to and constraints faced by people living on or below the poverty line [38]. MTM is an internet-based tool that asks participants to emulate a person living in poverty by making a series of choices towards completing tasks over a span of 30 days. As participants complete tasks, stress levels are simulated as short-term consequences of choices. Deferring actions have long-term consequences through visual cues and a three-strike system when too many unmet needs accumulate over time.

Like the WS project, the work of Bogo et al. relies on actors as a teaching tool, but rather than teaching the community, this work trains and evaluates social worker students, recent graduates, and experienced practitioners [28, 27, 153, 77]. Human actors are instructed to play a client interacting with a student during a simulated interview. Follow-up structural reflection and debriefing interviews are used to help with a student's control over their own emotional or biased responses. This approach has been shown to greatly benefit students having trouble drawing links between theory and practice or controlling their emotions when working with clients.

[16]Make The Month: *http://www.makethemonth.ca/*, *http://www.uwaykw.org/make-the-month/*.

2.5.2 Virtual Environment

Virtual reality (VR) is a sophisticated computer application that allows participants to view and interact with a simulated environment in such a way as to minimize the separation between the real and simulated worlds. In addition to entertainment applications, VR has allowed researchers to extend experiential learning to treating phobias through exposure therapy, mastering new medical aids such as wheelchairs, and practicing better behaviour-management skills [233].

Behaviour-management has been the area of research most closely applicable to the homeless population, especially for at-risk youth. The multimedia Smart Talk (ST) software tool was developed for social workers to teach clients new strategies for resolving conflict without violence [31, 32]. Users interact with simulated scenarios that increase their knowledge about relevant nonviolent strategies and "anger triggers." The project relied on well-researched factors impacting client learning: awareness, beliefs, efficacy, intentions, and aggression. For a variety of reasons, this approach has been most successful with at-risk youth in addressing issues from ADHD and anxiety to autism-spectrum disorders. Hence its application and future development have focused on these demographics [263, 8].

2.5.3 Virtual Patients

A virtual patient (VP) in social sciences is designed to train clinicians and mental health providers skills needed for patient interviewing, assessment, and diagnosis. Kenny et al. developed a VP system that assesses a social work student's ability to diagnose a veteran with post-traumatic stress disorder (PTSD) [130]. It is meant to overcome some of the limitations of using actors by having the student interact with a virtual Navy veteran. This work has been extended to other experiential learning applications, including motivational interviewing, interviewing skills for veterans, and clinical trials in other domains [194, 205].

2.5.4 Multi-Agent Simulation

The most common use of multi-agent simulations (MAS) in the social service domain has been for policy evaluation. MAS provides the opportunity for policy makers to try different "what-if" scenarios under different agent-behaviour or service-delivery scenarios. The underlying agent behaviour often relies on the rational-agent economic model [26].

In the social service domain, large-scale agent-based simulations try to close the gap between program trials at a local level and their implementation as policy on a larger scale. Due to the complexity of human behaviour and scaling to thousands of agents, agent behaviour trials have been limited to a small number of client characteristics. Agent behaviour can be emulated using a probabilistic model that mimics decisions made by a particular portion of a population under past policies. Social science models of behaviour can be used if the target population abides by the same social norms and structural factors as the population used to build the model.

Predicting the effectiveness of a single policy can be difficult due to the great number of uncertainties and contingencies that need to be included in the model. Instead, Beeler et al. used MAS to test the effectiveness of combining two separate policies in tackling an influenza pandemic outbreak, a mass vaccination policy versus voluntary self-quarantine [22]. This simulation incorporates agent-based modelling to characterize the behaviour of patients. In addition to their age and the type of neighbourhood in which they were placed, the patient model decision was limited to rates of voluntary self-quarantine.

Pandemic characteristics consisted of average days a person is contagious, the degree of infectiousness, and the risk of death from infection. The study shows that the effectiveness of a public health policy might be dependent on other interventions used in parallel and on the epidemiological properties of the pandemic. Specifically, having a combination of voluntary and involuntary approaches is best overall. This result highlights the need for considering multiple factors when making policy and evaluating related programs.

Harpring et al. use discrete event simulation to maximize resource usage, minimize client wait times, and find new resources required to meet the needs of clients visiting a shelter providing health and family services [106]. The simulation revealed a new configuration that reduces the intake count by one out of five, achieving an overall efficiency gain for the shelter without negatively impacting clients. It also produced a predictive model to prepare the shelter for an increase in client intake rates. The results of the study were significant enough that the shelter implemented many of its recommendations.

Much of the research around simulating decisions of social services clients has relied on the rational agent model. Common factors included in such simulations are the quality and quantity of affordable housing and socioeconomic factors that contribute to its provision [181]. A 1999 study simulates the impact that changes in housing policy will have on people living at or below the poverty level, based on a model of housing demand versus housing availability and income levels [68]. Despite being an older study, it considers more client characteristics than most recent simulations and relies on technology and methodologies comparable to those in use today. The policy makers controlled the quality, availability, and pricing of homeless shelters in the simulation. Agent characteristics were made up of economic motivators and constraints. The probability of being homeless was based on household income and the lowest level of quality of housing available. Attributes used for the agent profiles were age, sex, number of people in a household, white versus non-white head of household, monthly income, and the Center for Epidemiologic Studies Depression Scale. It was hypothesized that greater depression leads to a higher probability of being homeless. Weather was considered a factor where lower temperatures increased the need for housing.

2.5.5 Social Service Ontologies

Several ontologies of social services exist, but are service-oriented modelling processes and constraints of the service provider. The lack of a high-fidelity client representation makes them inappropriate for use in BRAMA and client-centric emulation. In each of these ontologies, the client interacts with the system in a transactional fashion. No special focus is placed on the nature and impact of that interaction on the client.

The Shelter Ontology for Global City Indicators (GCI) provides metrics for measuring and comparing city performance [259]. A homeless person is represented as being either absolutely or relatively homeless[17]. Client needs are limited to obtaining housing, with several types of housing being identified as suitable for absolutely or relatively homeless clients. The INSPIRE ontology is focused on processes and resources of the service provider [195]. A client may have a physical need, a social need, or a combination of the two. Each need also has an urgency associated with it. Depending on the type of need, the client is passed to appropriate departments. A department offers a service that satisfies that need. A service

[17] The GCI ontology adopts the definitions defined by UN-Habitat: "Absolute homelessness occurs when there is neither access to shelter nor the elements of home. A person may be in relative homelessness; that is, they may have a shelter but not a home" [254].

has constraints on resources and required documentation from a client. Finally, the Open Eligibility Project is a taxonomy of services offered to clients, but no details about client needs are included [11].

2.6 Observations

This chapter presented state-of-the-art research that can be used to emulate the complex behaviour of homeless social service clients. Unfortunately, each approach lacks the ability to consider many unobserved factors. At the same time, there are many factors identified in the social science literature that are under-represented by the AI research community in modelling human behaviour.

2.6.1 Existing Models of Human Behaviour

There are a number of models of rational decision making. Each has its own limitations, lacking the expressiveness or completeness required to emulate human behaviour. Current social science models focus on observed behaviour, with a number of theories that identify factors that may lead to seemingly irrational behaviour, including irrational and emotional beliefs and desires, as well as normative social factors [74, 274, 141].

Economic theories have a binary understanding of rational behaviour, relying on the rationality principle to categorize any behaviour that does not maximize utility as irrational. Within behavioural economics, Tversky and Kahneman characterize the limitations of a rational agent as a framing problem where required information is excluded from the agent, resulting in observable biases [251]. It presents a well-studied and empirically validated theory of how humans actually make decisions. However, while a viable alternative to modelling non-rational agents, behavioural economics is not a serious alternative to the rationality principle as it lacks robustness, and it can only be applied to well-defined decision problems [26]. In goal-oriented AI system like AI planning, the need for providing goals, preferences, and assigning probabilities to actions *a priori* makes it difficult to represent the complexity of reasoning and dynamic nature of the environment of social service clients.

Bounded Rationality Natural limitations outlined by bounded rationality are not implemented directly by any system. While such limitations are acknowledged, existing AI research has focused on overcoming those limitations through various optimization techniques and improvements in efficiency. What is missing is a system that retains many of the limitations and biases exhibited by humans, to better emulate their actual behaviour. Amongst the many models of non-rational behaviour, there is little incentive for economists, outside of behavioural economics, to adopt bounded rationality over any other non-rational model [224].

Maslow's Hierarchy It is difficult to define a realistic goal ordering and preferences for rational agents using traditional representations. Grounding preferences in Maslow's hierarchy provides a theoretical [160], if not consistent, basis for goal ranking that overcomes some of the calculated desires and preferences in goal-based reasoning systems discussed in Section 2.4.4. The required axioms in decision theory and expected utility govern relationships between preferences used in utility maximization that do not always hold for human desires and preferences, such as altruism, reciprocity, and trust [223]. When the relationships do hold, preferences become contextualized in a situation and the type of decisions being made [9]. Hence, any agent whose preferences are not transitive would be considered irrational [26]. To simplify the modelling effort, most influential neoclassic economists treat preferences as stable or given [141]. In AI systems, goals are provided *a priori* as achievement goals. Any goals that are continuously reranked are explicitly defined as maintenance goals that support the satisfaction of achievement goals. As Maslow's hierarchy illustrates, however, human "maintenance goals" like eating and sleeping are also basic goals and need to be provided *a priori* as well. While Maslow's representation may be inefficient, as it adds an extra layer of abstraction, any human-centric system must consider this ordering as required regardless of any reduction in efficiency or optimization.

Emotions There are several limitations that make it difficult to incorporate existing theories of emotions. First, it is difficult to identify positive and negative valences of emotions in specific situations described by a client. Second, "drives" are a vague and dynamic representation of emotions, and most systems rely on a predetermined assignment of valence that statically associates a stimulus with a response [134]. Such models assume that emotions can be applied equally to all observed situations. However, an agent will respond differently to similar situations depending on its emotional mood. Sometimes it will be optimistic and have high expectations of success. At other times, the same situation may be viewed with pessimism, resulting in a low expectation of success. Such dynamism in an agent's emotional responses is not captured by existing models of emotions used by AI systems. Models employed to analyze behaviour of social service clients as autonomous agents lack information about the client's beliefs and constraints for individual decisions. At the same time, the agent's reasoning relies on calculations based on its assumed internal state. Such models do not sufficiently capture the temporal dimension and continuous nature of emotions, and may benefit from a utility function based on the ECOC theory. ECOC generalizes the agent's overall progress in executing a plan over time and does not need to know what stimuli triggered an observed action, only that over time behaviour changes according to a pattern found in the graph.

Existing AI Systems AI applications would benefit from incorporating social science theories like Maslow's hierarchy that ground human achievement goals and their ranking in line with basic human needs [160]. AI planning provides a systematic and rational process for generating a search tree that includes objectively possible decisions rather than subjectively probable decisions like decision trees. However, key limitations still exist.

First, most systems focus on creating and executing plans in the most efficient way while minimizing or ignoring human limitations and bounded rationality [137, 69]. Second, human-like cognitive impairments caused by faulty memory and cognitive biases are not easily captured [103]. Some research into simulating certain types of impairments exists with episodic memories and incomplete information [59, 179]. However, it would be infeasible to generalize such results to whole populations, especially those under-represented in such studies. Also, associating positive and negative valences with specific actions ignores the complexity of human emotions, relying on social norms rather than unique biases of individuals. Hence, existing definitions of agent "drives" are too vague and inflexible to represent human emotions [134].

Lack of Data Collecting data from various sensors in a system is a reliable form of building and verifying models. Increasingly, metrics for city services are being developed as part of a move towards "smart cities" [87]. Except for clients in extreme cases or requiring immediate emergency services, most information known about individual clients is qualitative rather than quantitative, obtained through interviews or questionnaires as part of a treatment or study [35, 178, 197]. This information captures the client's life experiences as a sequence of events, choices, perceived factors, and emotional states. However, without a considerable amount of thematic analysis to evaluate and code the data, AI systems lack the models and metrics to interpret this limited data in order to successfully monitor and predict behaviour of clients using social services [171].

2.6.2 Conclusion

Due to limitations placed on the agent and the observer, understanding human behaviour from observations requires a combination of subjective and dynamic choice theory. Jeffrey's decision theory, for example, provides the framework for representing and calculating utility for different scenarios that satisfy an agent's goals. Relying on dynamic choice theory, decision theories can be used to interpret unusual behaviour, like an agent exhibiting both myopic and resolute behaviour. The questions are: Which type of strategy is the agent deploying? What goals is it pursuing? What role do long-term versus short-term goals play in choosing a strategy? Due to bounds placed on the observer, it would be impossible to iterate through all combinations of an agent's likely preferences and factors to predict its behaviour. Without grounding the agent's preferences in something concrete, it would be nearly impossible to infer those preferences directly.

In the next chapter, the groundwork is set for a new architecture that combines classical views on rationality with human-centric utility calculations. The presented system provides a state-of-the-art architecture for creating a high-fidelity model of homeless client emulation. A human-centric utility function is presented that grounds goal utility in Maslow's hierarchy, while action utility is based on the emotional state of the agent.

Chapter 3

Human-Centric Single Decision Making

3.1 Introduction

Rational human decision making differs from the ideal proposed by rational agent theory in that it may seem to fail to maximize utility. This thesis argues that a human agent is in fact rational, but uses different goals and preferences than an observer uses to assess the agent's rationality. This chapter introduces the first part of the **B**ounded **R**ational **A**gent **M**otiv**A**tions (BRAMA) framework, extending single decision theory to include dynamic human-centric factors. BRAMA relies on a rational reasoner to choose an option with the highest calculated expected utility. Utility calculation is bounded by missing or incomplete information about available actions and possible goal propositions. The calculation of goal utility is grounded in Maslow's hierarchy of needs [160]. The calculation of an action's expected utility is based on an emotional evaluation of the action's expected probability of success that differs from classical decision theory. Several equations are presented for calculating goal and action utility. Two axioms BR-1 and BR-2 explicitly state the relationship between ranking and preferences of goals.

3.2 Bounded Rational Agent MotivAtions (BRAMA)

The BRAMA framework is meant to emulate decisions made by a seemingly irrational human-like agent with the use of a rational reasoner. In this chapter, BRAMA extends a single decision rational reasoner using a utility function that incorporates rational and non-rational factors influencing human decision making.

For single decision making, BRAMA represents a domain as a state and a set of actions along with related terms listed in Table 3.1. The state S_t is a set of propositions that represent what is true about the agent and its environment at a particular time step t. An individual proposition s_i is true at time step t if $s_i \in S_t$. S_0 is the set of initial propositions true in the world at time step $t = 0$. S_t^y is a subset of S_t at some time step t indexed by y. An action a_m transitions one state to another, where $exec(a_m, S_t) = S_{t+1}$. The complete set of actions possible is AS, where $a_m \in AS$. Each action a_m has precondition set PRE_m, a set of propositions that must be true *before* the action can be executed, where propositions $pre_{m,i} \in PRE_m$. Each action also has an outcome set OUT_m, a set of propositions that must be true *after* the action is executed, where each proposition $out_{m,i} \in OUT_m$, and $OUT_m \subseteq S_{t+1}$ after executing $exec(a_m, S_t)$. A sequence of actions is A^x, where x is a unique sequence index, starting at some state of the world S_t.

In single decision theory, as discussed in Section 2.3, future actions and outcomes are independent from past actions and outcomes. The outcome of a choice is true if the choice was made and not true if the choice was not made. Each individual action is viewed as an alternative action, and each outcome as an independent alternative outcome [105]. For example, either a person decided to go for a stroll with an umbrella, without an umbrella, or did not go for a stroll at all. Imagine they went for a stroll. If it was not raining, the outcome is a state where the person went on a stroll, has an umbrella, and enjoyed the stroll. If it was raining and they did not bring an umbrella, then the outcome is a state in which they went on a stroll, did not have an umbrella, and did not enjoy the stroll.

The nature of outcomes in single decision theory can be put more strongly: the outcomes of alternative choices are mutually exclusive of other choices available or will be available in the future. There are several ways to interpret choices and outcomes, as discussed in Section 2.3.1. For example, like expected utility theory (EU), prospect theory (PT) also considers choices as mutually exclusive. However, unlike EU, there is no extension to PT that provides support for a time dimension and interdependence of choices. Hence, decision theory incorporated in BRAMA is based on the EU model of utility and decision making. Consider an agent at time step t that has a choice to execute some actions a_m, a_n, and a_o, where the outcomes are mutually exclusive with $OUT_m \neq OUT_n \neq OUT_o$. If action a_m is chosen the outcome propositions are $OUT_m \subseteq S_{t+1}$, where $OUT_n \notin S_{t+1}$ and $OUT_o \notin S_{t+1}$. If action a_n is chosen the outcome propositions are $OUT_n \subseteq S_{t+1}$, where $OUT_m \notin S_{t+1}$, and $OUT_o \notin S_{t+1}$. Finally, if action a_o is chosen the outcome propositions are $OUT_o \subseteq S_{t+1}$, where $OUT_m \notin S_{t+1}$ and $OUT_n \notin S_{t+1}$. Any future actions are also independent of previous actions, meaning no propositions are removed, only added with the outcome propositions of the chosen action at time step t.

A BRAMA agent is a goal-driven decision maker, where the agent's reasoning, environment, goals, and actions dictate the action selection process. A goal is a proposition where the agent cares about its truth assignment, meaning whether the proposition is true or false. A goal utility represents how meaningful the goal is to the agent. An action utility represents how meaningful an action is to an agent. An action probability represents how likely an agent perceives an action to successfully satisfy its goal propositions. BRAMA has additional terms that influence how actions are chosen for single decision theory, listed in Table 3.2. A reasoner decides which action is chosen for immediate execution at time step t. The search space is a set of all the possible states that can be true at time step $t+1$ given the current state of the world and outcomes of available actions.

Table 3.3 lists terms required to define a BRAMA agent for single decision theory. $S\text{-}BR$ is a version of the state of the world the agent believes is true. $S\text{-}BR_t$ is the version the agent believes is true at time step t, which may be the current time where $S\text{-}BR_t = S\text{-}BR$, or it may be at an earlier or later time. G is a set of goal propositions an observer believes the agent should want to be true. $G\text{-}BR$ is the set of propositions the agent actually wants to be true. Propositions in set $G\text{-}BR$ are analogous to an outcome o_i in Section 2.3.4 that is not a ϕ_i proposition, meaning the agent cares about them being true and believes it has control over them being true. $G\text{-}BR_t^U$ is the set of goal propositions the agent considers unsatisfied at time step t. $G\text{-}BR_t^S$ is the set of satisfied goal propositions, where $G\text{-}BR_t^S \subseteq S\text{-}BR$ and $G\text{-}BR = G\text{-}BR_t^U \cup G\text{-}BR_t^S$.

The set $AS\text{-}inc$ is a set of incorrect actions that have the same label ("visit shelter," "book appoint-

Table 3.1: BRAMA domain representation terms for single decision theory

Term	**Description**
S_t	State of the world, meaning what propositions are true at time step t.
S	Set of states of the world, where $S_t \in S$.
s_i	Proposition with a truth assignment at some time t, where $s_i \in S_t$ means s_i is true at time step t.
AS	Set of available actions, where $a_m \in AS$.
S_t^y	Subset of propositions true at time t, where $s_i \in S_t^y$ and $S_t^y \subseteq S_t$, so that $s_i \in S_t$.
A^x	Sequence of actions with a unique index x, starting at some state of the world S_t.
action (a_m)	Action (a_m) with outcome propositions OUT_m that transitions one state (S_t) to another (S_{t+1}).
a_k^x	Some action $a_m \in A^x$ at position k, meaning action a_m is the k-th action to be executed in the sequence A^x.
$exec(a_m, S_t)$	This procedure executes action a_m to transition S_t to S_{t+1}, where $exec(a_m, S_t) = OUT_m$ and $OUT_m \subseteq S_{t+1}$.
PRE_m	Set of propositions that must to be true immediately before action a_m can be executed, where $PRE_m \subseteq S_t$ if a_m is executable at time step t.
$pre_{m,i}$	A proposition indexed by i that must be true for an action a_m to be executable, where $pre_{m,i} \in PRE_m$.
OUT_m	Set of propositions that need to be true immediately after action a_m has been executed, where $OUT_m \subseteq S_{t+1}$ if a_m is executed at time step t.
$out_{m,j}$	An outcome proposition indexed by j that needs to be true immediately after action a_m is executed, where $out_{m,j} \in OUT_m$.

Table 3.2: BRAMA action selection terms for single decision theory

Term	**Description**
agent	An autonomous entity.
reasoner	A systemic action selection process.
search space	Subset of states S that are accessible from S_t with available actions in AS.
goal	A proposition the agent cares about being true.
goal utility	Utility assigned to a goal by an agent.
action utility	Utility assigned to an action based on the goal states it makes true.
action probability	Probability of action a_m successfully resulting in its outcome propositions in OUT_m being true.
knowledge	What an agent or observer knows about the current state of the world, goal propositions, and possible actions as well as the actions' preconditions and outcomes.

Table 3.3: BRAMA agent terms for single decision theory

Term	**Description**
t	Time step t where the current time step is at $t = 0$.
$S\text{-}BR$	State of the world the agent believes to be true.
$S\text{-}BR_t$	State of the world the agent believes to be true at time step t, either the current, past, or future time step.
G	A set of goal propositions the observer believes the agent should want to be true, where $G \notin S_t$.
$G\text{-}BR$	A set of goal propositions the agent wants to be true.
$G\text{-}BR_t^U$	A set of goal propositions at time step t the agent believes are not true but wants to be true, where $\varnothing = G\text{-}BR_t^U \cap S\text{-}BR_t$.
$G\text{-}BR_t^S$	A set goal propositions the agent believes are true (and satisfied) at time step t, where $G\text{-}BR_t^S \subseteq S\text{-}BR_t$.
$G\text{-}BR_t^{U+S}$	A set of all goal propositions for an agent at time step t, where $G\text{-}BR_t^{U+S} = G\text{-}BR_t^U \cup G\text{-}BR_t^S$.
$inc(a_m)$	A function that transforms a correct action a_m into an incorrect action, as defined in Equation 3.2.
$AS\text{-}cor$	A set of all correct actions, where $AS\text{-}cor \subseteq AS$.
$AS\text{-}inc$	A set of all incorrect actions, where $AS\text{-}inc \subseteq AS$.
$AS\text{-}BR$	Actions the agent knows about, where $AS\text{-}BR \subseteq AS\text{-}cor \cup AS\text{-}inc$.
$BR(I)$	Information available to the agent within its limited memory for storing knowledge about the state of the world, goals, and actions they know about, where $BR(I) = \{S\text{-}BR, G\text{-}BR, AS\text{-}BR\}$.
MH	A mapping between an agent's goal propositions and Maslow's hierarchy, based on data or provided *a priori*. The mapping establishing a goal order based on Maslow's hierarchy.
$pref$	The ordering for a set of goals, where $pref \in \{A, MH, x\}$ for the agent's preferred order, Maslow's order, and practical order after execution of sequence A^x and outcome O^x.
$rank(pref, s_i)$	Preference ranking for goal $s_i \in G\text{-}BR_t^U$ given some preference $pref$.
$exp(t)$	Neoclassical expected utility function with parameter t, where t is a time step for which expected utility is calculated.
$ecoc(x)$	Expected utility based on ECOC function, where $x = exp(t)$.
$execu$	Label to indicate which expected utility function is used to calculate utility of actions and sequences, where $execu \in \{exp, ecoc\}$ for neoclassical function $exp(t)$ and ECOC-based function $ecoc(x)$.
$u(pref, s_i)$	Cardinal utility assigned to the proposition s_i for some $pref$ ordering.
$u(execu, pref, s_i)$	Expected utility function for proposition s_i, where $execu \in \{exp, ecoc\}$ and $pref$ is some ordering.

ment") as actions in *AS-cor* but for which preconditions or outcomes are missing or added. The set of actions an agent knows about is *AS-BR*. It is a subset of the union of correct actions in *AS-cor* and incorrect actions in *AS-inc*. $BR(I)$ is the limited memory an agent uses to store knowledge: its beliefs about state of the world, goal propositions, and actions for use during the reasoning process. The function $exp(t)$ is the neoclassical expected utility function[1]. The function $ecoc(x)$ is an expected utility function based on the emotional cycle of change, defined in Equation 3.19 in Section 3.5.2.

Next, the order in which goals can be ranked is introduced. The preference used by an agent to rank goals is represented by the term *pref*, where $pref \in \{A, MH, x\}$. Preference MH is based on a set of mappings between specific goals in *G-BR* and levels of Maslow's hierarchy. The rank of a mapped goal, then, is the MH level mapped to that goal. For example, the goal "eat food" is mapped to the physiological MH level and has the highest rank of 1. The goal "have clothing" is mapped to the security MH level and has a goal ranking of 2. Next, an agent's preferred order is $pref = A$ indicating the preferred order of agent A. For example, an agent might prefer to "have clothing" over "eat food," especially when it has recently eaten or it is cold outside. This is a goal preference based strictly on the agent's own subjective preference of one goal over another.

Finally, the order in which goals are actually satisfied by some sequence of actions is referred to as the "practical order." Due to environmental constraints, the actions required to satisfy goals may need to be done in an order that differs from the MH or agent's preferred order. For example, consider a shelter client who wants to "eat food" and "have clothing," and in that order. However, due to staffing limitations the soup kitchen does not open until after the clothing donation centre closes. Hence the client would need to obtain clothing first followed by a meal at the soup kitchen. One can also imagine such constraints made up of preconditions, where actions satisfy goals that are prerequisites of other actions that satisfy other goals. For example, visiting a furniture bank may require a referral from a social worker. Obtaining that referral must be executed before obtaining furniture at the furniture bank. Hence, the practical order would have "obtain referral" first followed by "visit furniture bank." Here, the practical order in which goals can be satisfied is based on some constraints imposed on the actions, resulting in some sequence A^x where $pref = x$.

3.3 Bounded Rationality

According to BR, there are three main types of bounds influencing an individual's decisions: information bounds, cognitive bounds, and time bounds [226, 227, 228]. Unlike other systems described in Section 2.4.3, BRAMA does not use methods to overcome such bounds for efficiency. Instead, BRAMA explicitly defines how these bounds inhibit agent decision making, and attempts to make rational decisions within these bounds. The limited representation for the state of the world, goals, and actions in the agent's memory $BR(I)$ prevents the agent from exploring all potentially useful actions during the reasoning process.

3.3.1 Information Bound

The bounded memory to store knowledge $BR(I)$ limits the number of goals, true propositions in S_t believed to be true, and actions that the client can retain at any one time. Limiting the amount of

[1]The utility function $exp(t)$ is not to be confused with the familiar exponential function e^x.

knowledge stored leaves the agent's knowledge in a state of incompleteness. Over time, the agent may also acquire knowledge that is incorrect without the ability to correct it. Recall that knowledge an agent believes to be true at time step t is $S\text{-}BR_t$. Say an agent executed an action that adds new propositions about the world the agent did not know before. For example, consider an agent with a goal of "create résumé" and the action "visit vocational worker" that has, as a subset of its outcome, the proposition "résumé workshop tomorrow at noon." After executing the action, this proposition is now included in $S\text{-}BR_{t+1}$, and the agent has "learned" a new belief. However, the new proposition may be true or false, and learning a false proposition causes the agent to have incorrect knowledge. This incorrect knowledge can then be used to execute incorrect actions. For example, if the information about the résumé workshop was wrong, causing actions based on this belief to be incorrect, then going to where the workshop was supposed to take place at noon would not satisfy the agent's goal of "create résumé." In general, any beliefs made up of a conjunction of propositions in some subset of $S\text{-}BR$ may be correct and incorrect. Any actions in $AS\text{-}BR$ and goals in $G\text{-}BR$ based on correct or incorrect beliefs may themselves be correct or incorrect as a result. This section provides definitions for different states of an agent's beliefs, actions, and goals.

Before continuing with the definitions, a quick note about forgetting knowledge. In addition to learning knowledge, an agent may also forget existing knowledge over time. Forgetting or more generally removing knowledge is not applicable in single decision theory since choices are independent and mutually exclusive, as discussed at the beginning of Section 3.2. Any negated terms are included in the belief, precondition, and outcome propositions. These include "did not bring umbrella" and "is not raining." The complete definitions provided here include different states of knowledge, but the process of removing knowledge is not applicable until discussions in Chapters 4 and 5 where action outcomes are not necessarily independent or mutually exclusive. Here, the consequences of actions are not independent and mutually exclusive outcomes but postconditions, set of propositions that can be to or deleted from the agent's beliefs. Hence, executing a "learning" action that deletes a proposition from $S\text{-}BR$ that is true in S_t is equivalent to forgetting correct knowledge. For the following definitions, the consequences of some action a_m will be referred to as ADD_m for a set of propositions added to S_t immediately after executing action a_m. ADD_m is the equivalent of outcome OUT_m for single decision theory. For the definitions to also apply to sequential decision theory and AI planning in Chapters 4 and 5, DEL_m will be a set of propositions that are deleted from S_t immediately after executing action a_m.

3.3.2 Knowledge in Bounded Memory

The knowledge stored in $BR(I)$ is made of correct, incorrect, missing, and alternative beliefs about the state of the world, as well as actions and goals. What an agent believes to be correct and incorrect plays a key role in how its actions and goals are interpreted by the observer. While the finite nature of memory explains why knowledge may be missing or incorrect, this section expands on the type of knowledge that may be missing or incorrect. We begin the discussion with some definitions.

Correct beliefs in $S\text{-}BR_t$ form a subset of S_t, namely the subset $S\text{-}BR_t \cap S_t$. Any other beliefs are incorrect. Correct actions make up the set $AS\text{-}cor$, while incorrect actions make up the set $AS\text{-}inc$. The union of these actions make up the set AS of all possible actions, as defined in Equation 3.1:

$$AS = AS\text{-}cor \cup AS\text{-}inc \tag{3.1}$$

where $\varnothing = AS\text{-}cor \cap AS\text{-}inc$. The function $inc(a_m)$ transforms a correct action a_m to an incorrect action a_n, as per Equation 3.2. Its inverse $inc^{-}()$ converts an incorrect action to its correct equivalent.

$$a_n = inc(a_m), \text{ where } (PRE_m \neq PRE_n) \text{ or } (ADD_m \neq ADD_n) \text{ or } (DEL_m \neq DEL_n) \tag{3.2}$$

The agent's knowledge about actions then is defined as:

$$AS\text{-}BR \subseteq AS\text{-}cor \cup AS\text{-}inc. \tag{3.3}$$

Finally, the agent's reasoner relies on actions available in $AS\text{-}BR$ to satisfy goals in $G\text{-}BR^U$, given what they know about the world in $S\text{-}BR$. The final bounded knowledge the agent uses is $BR(I)$ defined as:

$$BR(I) = \{S\text{-}BR, G\text{-}BR, AS\text{-}BR\}. \tag{3.4}$$

State of Beliefs

Correct beliefs in $S\text{-}BR_t$ form a subset of S_t, namely the subset $S\text{-}BR_t \cap S_t$. **Incorrect beliefs** are those that an agent believes are true but are not. An incorrect belief is a proposition s_i if:

$$(s_i \in S\text{-}BR_t) \wedge (s_i \notin S_t). \tag{3.5}$$

A **missing belief** is a proposition or set of propositions an agent needs to satisfy its goals but that are not elements of $S\text{-}BR_t$. Given a goal proposition s_j, a belief proposition s_i is a missing belief if:

$$(s_i \notin S\text{-}BR_t) \wedge (s_i \in S_t) \wedge (s_i \in PRE_m) \wedge (s_j \in ADD_m) \wedge (s_j \in G\text{-}BR_t), \tag{3.6}$$

where a_m is an action that satisfies the goal proposition s_j. **Alternative beliefs** are those that independently allow an agent to satisfy its goals through some action. Given a goal proposition s_k, alternative beliefs are propositions s_i and s_j if:

$$\big(\{s_i, s_j\} \subseteq (S\text{-}BR_t \cap S_t)\big) \wedge (s_i \in PRE_m) \wedge (s_j \in PRE_n) \wedge (s_k \in G\text{-}BR_t^U) \wedge \big(s_k \in (ADD_m \cap ADD_n)\big), \tag{3.7}$$

where s_i must be true before executing action a_m, s_j must be true before executing action a_n, and both actions can independently make the goal proposition s_k true.

State of Actions

An agent's **correct actions** are simply those that exist in $AS\text{-}BR \cap AS\text{-}cor$. **Incorrect actions** are actions in $AS\text{-}BR \cap AS\text{-}inc$, as defined in Equation 3.2. Here, either preconditions or outcomes are incorrect. Any action with incorrect outcomes will ultimately fail to satisfy goal propositions the agent believes will be made true by the action. For example, say an agent has a goal of "finding a job" and believes executing the action $a_m = request(job, shelter)$ at any local shelter has a consequence (ADD_m) of "obtain available vocational counselling." Unfortunately, the local shelter does not offer this service, and the inaccurate ADD_m causes action a_m to be incorrect. To an observer, actions with incorrect outcomes can be executed, but will seem excessive or unnecessary. For example, going to a shelter with extra services that a client needs but with longer wait times may seem irrational if a smaller shelter that only offers services the client uses is closer and has shorter wait times.

Incorrect preconditions make any attempt at an action futile for the agent. For example, consider an agent that is hungry. Hot meals are available at a soup kitchen, say action $a_m = get(food, soup\_kitchen)$. However, the agent is only aware of action a_n, where $a_n = inc(a_m)$ and PRE_n does not include the precondition of registering with social worker before securing a spot. The agent needs to update its knowledge about the precondition PRE_n or find another action to obtain food. An observer may also find it irrational when an agent chooses an action that is not possible or suitable for known goals.

Missing actions are those the agent could use to satisfy goals but does not know about. An observer may find it irrational that an agent used one action over another that is more suitable, not realizing that the more suitable action is not a member of $AS\text{-}BR$ or was forgotten if it was used before. Also, any consequences of forgotten actions are no longer associated with the agent's existing goals in $G\text{-}BR^U$, meaning the agent no longer knows that the forgotten action can satisfy the agent's goals. For example, an agent that is hungry and knows it can purchase food at some store may perform the action of "buy food at store X." The agent may not be aware of buying food at another store at a lower cost or visiting a food bank where food is free. Referring to an action as "missing" implies that it is not in memory but would be useful if it was in memory. Hence, actions that are not in memory but do not satisfy any of the agent's goals are not considered missing. An action a_m is missing if:

$$(a_m \notin AS\text{-}BR) \wedge (ADD_m \in G\text{-}BR^U). \tag{3.8}$$

Finally, **alternative actions** are correct actions available to the agent in $AS\text{-}BR$. They are executable at state S_t and equally contribute to an agent's goals $G\text{-}BR^U$. Actions a_m and a_n are alternative actions if:

$$\big(\{a_m, a_n\} \subseteq AS\big) \wedge \big(m \neq n\big) \wedge \big((PRE_m \cup PRE_n) \subseteq S_t\big) \wedge \big((ADD_m \cup ADD_n) \subseteq G\text{-}BR^U_t\big). \tag{3.9}$$

A key difference between incorrect, missing, and alternative actions to an observer is the perception of the agent. The agent would be perceived as indifferent to alternative actions, but incorrect when using incorrect actions or not using missing actions. If an agent is observed to use different alternative actions, this would be a clue to the observer that these are alternative actions rather than the agent having incorrect or missing actions in $AS\text{-}BR$.

State of Goals

To an observer, correct goals G are those deemed by the observer as ones the agent should have. However, **correct goals** according to the agent are propositions added to $G\text{-}BR^U_{t+1}$ that contribute to existing goals in $G\text{-}BR^U$. A goal proposition s_i in PRE_m is correct if:

$$\big(s_i \in (PRE_{m,i} \cap G\text{-}BR^U_t)\big) \wedge \big(\varnothing \neq (ADD_m \cap G\text{-}BR^U_t)\big). \tag{3.10}$$

Incorrect goals are goals the agent is pursuing but should not be. Incorrect goals are goal propositions an agent adds to $G\text{-}BR^U_t$ that do not contribute to satisfying existing goals in $G\text{-}BR^U_t$. For example, hunger is a sensation caused by a low blood sugar level, and "reducing hunger" is a subgoal towards "increasing blood sugar level." Here, eating food is a possible action that satisfies both goals of reducing hunger and the main goal of increasing blood sugar level. However, "reducing hunger" can be perceived in two ways, as a long-term goal that actually reduces hunger or as a short-term goal that simply suppresses the feeling of hunger. If an agent only acts on the subgoal "reducing hunger," without increasing its blood sugar level, alternative methods to eating are sufficient. For example, suppressing the feeling of hunger can be achieved by consuming appetite suppressants such as smoking [43] or drinking aerated drinks or caffeine [167, 120]. A goal proposition s_i in PRE_m is incorrect if:

$$\big(s_i \in (PRE_{m,i} \cap G\text{-}BR_t^U)\big) \wedge \big(\varnothing = (ADD_m \cap G\text{-}BR_t^U)\big). \tag{3.11}$$

A possible consequence of having incorrect or missing actions is that of having incorrect or missing preconditions for satisfying existing goal propositions. This introduces the idea of **missing goals**. Missing goals are propositions the agent does not know about, which are preconditions for actions that satisfy its goals. For example, to execute the action "buy food," its precondition "have money" must be true. If an agent does not have money but goes to the store to "buy food," having money is a missing goal. For a non-goal proposition s_i and a goal proposition s_j, s_i is a missing goal proposition if:

$$(s_i \in PRE_m) \wedge (s_j \in ADD_m) \wedge (s_j \in G\text{-}BR_t^U) \wedge (s_i \notin G\text{-}BR_t^U). \tag{3.12}$$

Finally, incorrect and missing goals are different from alternative goals. **Alternative goals** are subgoals an agent knows about, and either allow the same or alternative actions to be executable. Sub-goal propositions s_i and s_j are alternative goals if, for some actions a_m and a_n and some goal s_k:

$$\big(s_k \in G\text{-}BR_t^U\big) \wedge \big(s_k \in (ADD_m \cap ADD_n)\big) \wedge \big(n \neq m\big) \wedge \big(s_i \in (PRE_m \wedge s_j \in PRE_n)\big). \tag{3.13}$$

3.4 Goal Ranking and Maslow's Hierarchy

In this section, BRAMA's framework for representing and ranking goals is introduced. The focus is placed on what is observable by a bounded observer. To a bounded observer, it is not always clear from observations alone what an agent's preferred goals are or how it obtained them. For human-like agents, BRAMA relies on Maslow's hierarchy to categorize and rank preferences using each MH level [160]. Each goal is first categorized as a goal type, then mapped to one or more MH levels. The mapping is not arbitrary, and is required to be domain-specific and unique to an agent's configuration.

Inferring goal preferences from observations is made more difficult because preferences are internal to the agent and often require the observation of a sequence of actions that satisfy some goals before an observer can infer the agent's goal preference. This section proposes methods for assigning preferences to goals based on Maslow's hierarchy. Recall from Section 2.3.4 that utility is associated with desires, and from Section 3.2 that desires are the goal propositions agents set out to accomplish. Hence, calculating a goal's utility is equivalent to calculating the preference of a goal. Recall also from Section 2.3.3 that DT has two types of utilities: ordinal, indicating a preferred order of choices, and cardinal, indicating the degree to which one choice is preferred over another. This section begins by presenting a method for mapping agent goals to Maslow's hierarchy. It then presents a general goal ranking framework for calculating ordinal and cardinal utilities for goals that are based on different types of MH mappings.

3.4.1 Basic Semantics of Goal Mapping

Goals can be mapped to MH levels directly, through functional, conditional, or domain-specific prerequisites. Some goals span multiple levels simultaneously, while others are mapped to different levels provided certain conditions are true. Whatever the case may be, we need a language to organize human goals, basic Maslow's needs, and goal interdependencies relating actions within a particular domain. Each domain will be different in the amount of reliable information available, hence goals and means will be framed differently. Here we discuss the basic semantics for representing goals and means required for emulating human decision making.

Goal Relation Types

Deciding how to map expressed goals to more abstract human needs is not a straightforward process. Some goals map to multiple needs. Others map to different needs under different conditions. Here we introduce basic goal semantics, illustrated in Figure 3.1, that help identify how to map goals, how to recognize potentially problematic mappings that may not lead to maximizing an agent's utility, and which mappings may be perceived differently by the observer and agent. The semantics presented here are domain independent, and are meant to guide a formal process of organizing goals based on some abstract goal representation specific to the application's domain. Maslow's hierarchy is used for grounding human-centric needs.

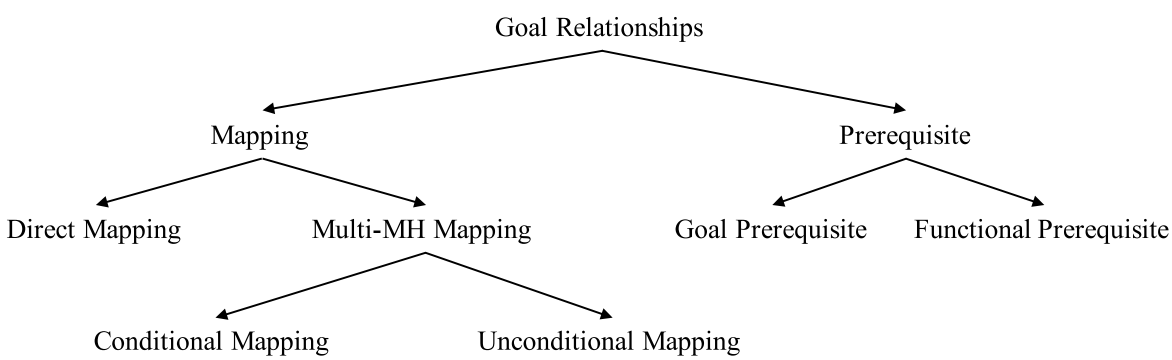


Figure 3.1: Goal relation semantics

Maslow's basic needs are organized in a hierarchy, meaning that mapping an individual's goals to an MH level automatically ranks them by that hierarchy. Hence the first type of relation, called the **mapping relation**, maps goals to MH levels. The second type is the **prerequisite relation** and captures known causal orderings between goals which indicate that one goal is a prerequisite of another. The relations are described in Table 3.4.

Consider an agent representing a social service client whose goals span each level of Maslow's hierarchy. The agent has a combination of possible goals, such as: be healthier, receive vocational training, find housing, have a better job, and don't be hungry. Relying on goal relations in Table 3.4, Figure 3.2 illustrates how each goal is mapped to an MH level and other goals.

A *direct mapping* associates a goal with a single MH level. For example, a goal of having friends or family is directly mapped to the social MH level. Training and getting a better job are both esteem-level needs. Being healthy and not being hungry are both physiological needs. Mapping relations can

Table 3.4: Goal relation semantics

Goal Relation	Label	Description
$dm(s_i, L)$	Direct Mapping	Associates a goal proposition s_i with a single MH level in L (e.g. "have a family" is a social goal).
$cm(s_i, L)$	Conditional Mapping	Associates a goal proposition s_i to one or more MH levels in L depending on some condition being true in S-BR, resulting in two or more separate goal propositions in G-BR for different MH levels (e.g. "have a phone" is a security goal for elderly agents and a social goal for a non-elderly agent).
$um(s_i, L)$	Unconditional Mapping	Associates a goal proposition s_i to two or more MH levels in L without a condition, resulting in two or more separate goal propositions in G-BR for different MH levels (e.g. "stay sober" is a self-actualization and a physiological goal).
$gp(s_i, s_j)$	Goal Prerequisite	A requirement placed on the agent to achieve one goal s_i before another goal s_j (e.g. having a job before a goal of having a *better* job). Both goals are mapped to an MH level.
$fp(s_i, s_j)$	Functional Prerequisite	A requirement placed on some goal proposition s_j to have some other goal proposition s_i be true before s_j for functional reasons (e.g. requirement to have an address before enrolling in a training program).

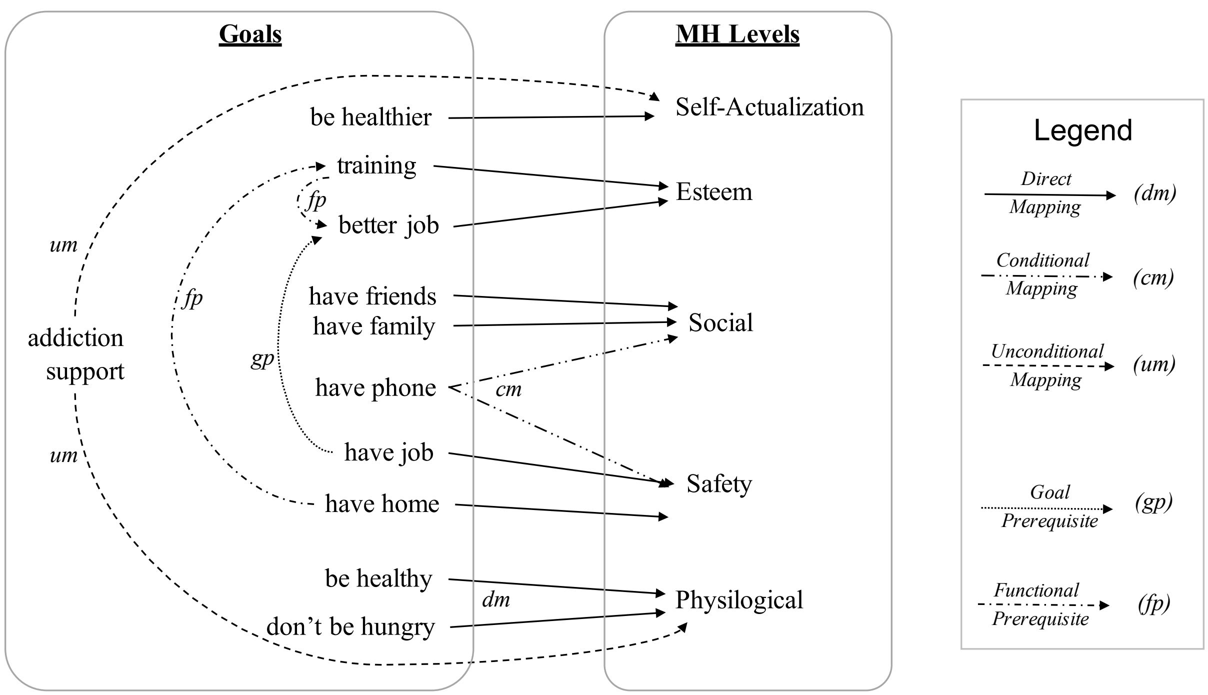


Figure 3.2: An example mapping MH for a social service client agent. For gp and fp goal relations, the base of the arrow is the prerequisite goal.

also go beyond the MH hierarchy to categorize and order goals that span multiple MH levels. *Multi-MH mapping* associates a goal with two or more MH levels and can be conditional or unconditional. Conditional mapping goals are applied to one or more MH level depending on some condition. For example, the condition can be based on a client's demographic: the need for a phone is a security need for elderly agents, and a social need for non-elderly agents. The condition can also be based on the underlying need being satisfied. For example, an adult's request for child care spans multiple MH levels that are associated with the child's needs rather that the adult making the request. For example, the need to have a happy family results in requests for toys or education, which are esteem needs. The need to have physically healthy kids results in requests for emergency child care, which are physiological needs. Unconditional mapping goals span two or more MH levels without a condition. For example, staying sober is both a self-actualization and a physiological need.

Next, a *prerequisite relation* associates a goal with other goals. A *goal prerequisite* is a requirement on the agent to achieve one goal before another where both goals are mapped to an MH level with $rank(s_i, MH)$. For example, having a job is a security MH level goal and a prerequisite for having a "better" job which is an esteem MH level goal. It is possible that a prerequisite relation may have been specified as an agent's preference for one goal before another: an implied ordering. In either case, separate actions satisfy each MH goal s_i and s_j. Given some goal propositions s_i and s_j mapped to MH levels, and actions a_k^x and a_l^x, the propositions are related by $gp(s_i, s_j)$ when

$$gp(s_i, s_j) \implies rank(MH, s_i) \wedge rank(MH, s_j) \wedge s_i \in PRE_k^x \wedge s_j \in OUT_l^x \wedge k < l. \tag{3.14}$$

Finally, a *functional prerequisite* captures requirements where one goal proposition makes it possible to satisfy another. Given some goal propositions s_i and s_j, where s_i is not mapped to an MH level, and actions a_k^x and a_l^x, the propositions are related by $fp(s_i, s_j)$ when

$$fp(s_i, s_j) \implies s_i \in PRE_k^x \wedge s_j \in OUT_l^x \wedge k < l. \tag{3.15}$$

For example, the goal of being in training has a requirement that the agent is housed before enrolling in a training program.

3.4.2 General Goal Ranking Framework

The general framework introduced here assumes goals have been ranked in some way. The source of that ranking is identified by the variable *pref*. Assuming goals are ranked based on mappings to Maslow's levels, we begin with *pref* = *MH*, where *MH* is a domain-specific mapping for some agent or group of agents. Once *MH* maps explicit goals to an MH level[2], we have a starting point for calculating goal utility. As discussed in Section 2.3.3, decision theory uses ordinal goal ranking to identify order, and cardinal goal ranking to identify the degree with which a goal is preferred over another. This section introduces calculations for both types of goal rankings.

Ordinal Goal Ranking

Ordinal goal ranking simply identifies the order in which goals are preferred. Mapping all expressed goals to basic MH needs orders them in line with the hierarchy. For *direct mapping* goals, the ordering follows

[2]The mapping to MH levels may relate to an abstract representation of basic goals or a specific request.

the hierarchy, with lower level goals being preferred. For *conditional mapping* goals, the final order depends on the condition being true. For *unconditional mapping* goals, a goal is split into more than one goal, each mapped to a specific MH level, and adopting that level's order. For example, in Figure 3.2, "stay sober" is both a physiological and a self-actualization goal. Each goal's level has a separate utility associated with it, the physiological goal having a higher utility than its self-actualization counterpart. The function $rank(pref, s_i)$ in axiom BR-1 is the numerical index of a goal's ranking, where *pref* is the preferred mapping and s_i is the goal. Note that the $s_i \succ_{pref} s_j$ relation indicates that goal s_i is mapped to a more preferred MH level than s_j. The numerical ranking $rank(MH, s_i) < rank(MH, s_i)$ expresses this quantitatively. Since preference ranking starts at 1 for preferred goals, the $\succ_{pref}$ is associated with the < sign between ranking goals, as per axiom BR-1.

Axiom BR-1 (Goal Level Ordering) For preferred mapping *pref*, all goal propositions s_i and s_j in *G-BR*,

$$rank(pref, s_i) < rank(pref, s_j) \iff s_i \succ_{pref} s_j. \tag{BR-1}$$

For Maslow's hierarchy where $pref = MH$, $rank(MH, s_i) \in \{1, 2, 3, 4, 5\}$ for each of the five MH levels. For directly mapped goals, $rank(MH, s_i)$ simply returns the MH level it is mapped to. For example, the goal for food is mapped to the physiological MH level, where $s_i = food$ and $rank(MH, s_i) = 1$. The goal for having friends is mapped to the social MH level, where $s_j = friends$ and $rank(MH, s_j) = 3$. For multi-MH mapped goal propositions, a separate goal proposition is introduced into *G-BR* for each MH level, each with its own $rank(MH, s_i)$ value. For example, the goal of "staying sober" requires two separate goals, say s_m for the physiological level and s_n for the self-actualization level, resulting in $rank(MH, s_m) = 1$ and $rank(MH, s_n) = 5$. For conditionally mapped goal propositions, a mapping is based on some condition being true in $S\text{-}BR_t$. For those mappings whose condition is true, a separate goal proposition is required for each MH level, similarly to the unconditional multi-MH mapping. Each new goal proposition has its own $rank(MH, s_i)$ value, reflecting Maslow's ordering relation $\succ_{MH}$ in

$$physiological \succ_{MH} security \succ_{MH} social \succ_{MH} esteem \succ_{MH} self\text{-}actualization.$$

Once the goal propositions are mapped, the appropriate goal ordering can be applied to the goal rank.

Cardinal Goal Ranking

Cardinal goal ranking indicates the degree of importance of a goal in relation to other goals. Recall that the ordinal ranking $rank(pref, s_i)$ is used to calculate whether there are preferred goals that should be satisfied before s_i. Continuing with MH order and $pref = MH$, since physiological goals are the most important, then while some physiological goal proposition s_j is still outstanding, any unsatisfied goal proposition s_i mapped to the higher social MH level should have a lower utility. The degree to which the utility of social level goal s_i is lower is relative to its distance from physiological level of goal s_j, as defined in

$$min(G\text{-}BR_t^U) = rank(pref, s_i), \text{ where for all } s_j \in G\text{-}BR_t^U, rank(pref, s_i) \le rank(pref, s_j) \tag{3.16}$$

and

$$u(pref, s_i) = 1 - \left(\frac{rank(pref, s_i) - min(G\text{-}BR_t^U)}{n - 1} \right)^{1/e} \tag{3.17}$$

where $rank(pref, s_i), min(G\text{-}BR^U) \in \{1, \ldots, n\}$ and n is the number of possible ranks.

To calculate cardinal utility when $pref = MH$ for an MH mapping, $u(pref, s_i)$ takes into account the MH level of goal proposition s_i in relation to the lowest outstanding MH level goal. The function $min(G\text{-}BR^U)$, in Equation 3.16 returns the minimum $rank(pref, s_i)$ from all outstanding goal propositions. Equation 3.17 then defines $u(pref, s_i)$, the cardinal utility of the goal proposition. The difference between $rank(pref, s_i)$ and $min(G\text{-}BR^U_t)$ is in the range $\{1, \ldots, n\}$, with $n = 5$ if $pref = MH$. The difference is taken to the power of $1/e$ to reflect logarithmic declining utility of goals at higher levels of the hierarchy. The inverse logarithmic exponent function is based on Bernoulli's original observation that a declining marginal utility for a desired asset follows a natural logarithm utility function rather than a linear one, and has been adopted by economists including von Neumann, Morgenstern, Savage, and others [258, 216]. The final value $u(pref, s_i)$ for $pref = MH$ is shown in Figure 3.3 (a), and has a range of $[0, 1]$. The utility of a goal proposition s_i diminishes more if its MH level is further from the lowest goal proposition's level. The more general case for any type of $pref$ ordering for zero to n goals has a continuous diminishing cardinal utility function, as shown in Figure 3.3 (b).

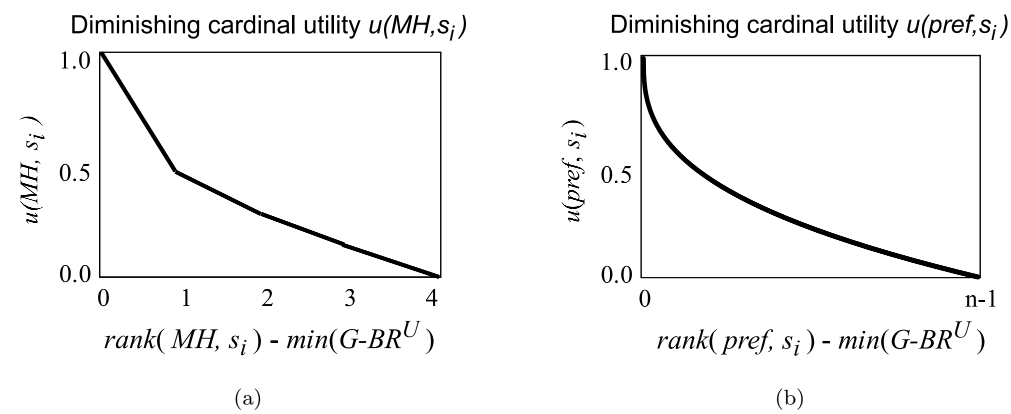


Figure 3.3: Diminishing cardinal utility relative to preferred order $pref$ for (a) five MH levels where $pref = MH$ and (b) the more general $pref$ from zero to n goals.

There is a direct connection between the ordering relation $\succ_{pref}$ and a goal proposition's utility. Specifically, the $u(pref, s_i)$ function in Equation 3.17 is a ranking for one goal proposition relative to another in a set of possible propositions. Suppose s_i and s_j are propositions in a set ordered by $\succ_{pref}$, then we can say that:

Axiom BR-2 (Preference-based goal utility is equivalent to *pref* order)

$$u(pref, s_i) \geq u(pref, s_j) \iff s_i \succ_{pref} s_j \iff rank(pref, s_i) < rank(pref, s_j). \tag{BR-2}$$

3.4.3 Inferring Preferences From Mapped Goals

Mapping goals to Maslow's hierarchy using goal relations demonstrates several benefits that assist in organizing an agent's preferences. First, MH levels provide a categorization and ordering of goal preferences grounded, to some extent, in behaviour psychology. The actual order of preferences may be in dispute [170, 128, 246], but a domain-specific mapping may provide valuable information about different types of mappings [111, 240]. A given domain-specific mapping MH may provide a categorization of goals that allows for clustering needs together in a meaningful way. This categorization can be used to organize resources in anticipation of other needs within the same MH level. Second, despite preferences initially expressed by a client, behaviour that does not satisfy goals in MH order during execution may reveal behaviour that does not maximize utility. Revealing such behaviour may identify agents that face external constraints not known to those evaluating agent behaviour.

Third, conditional mappings may reveal a correct mapping but wrong conditions assigned to an agent by the observer. For example, consider an agent representing a homeless client that requests a "phone" and a "referral" to the doctor. To the agent, both requests are equally important. To an untrained observer, a referral to the doctor is a physiological or security need but a request for a phone may be regarded as a less important social or esteem need. However, it can be argued that for an elderly client who is chronically homeless, having a phone is a matter of life and death, making it a physiological or security need rather than a social one. Also, the definition of an "elderly person" can be in dispute. In Canada, access to many financial assistance programs and health benefits is tied to the retirement age of 65 [133]. Hence many practitioners could assume that a 55 year old client is not an elderly client, and map the client's requests for a "phone" to social and esteem level. However, the physical and psychological strain of living on the street causes many clients to prematurely suffer the physiological symptoms usually associated with much older individuals [186]. It would be appropriate to treat such clients as elderly. Rather than mapping by age, a more appropriate mapping would be based on the "actual" state of the client. Such conditional mappings highlight situations where the observer's perception of the agent's situation and characteristics may lead to incorrect interpretation of goal ranking and behaviour. Such issues will be discussed further in Chapter 6.

3.5 Emotional Expected Utility

Subjective decision making, introduced in Section 2.3.4, highlights the limitations of classical decision making used to calculate expected utility in response to a dynamic environment. The preferences for goals and our perception of success changes over time, and objective expected utility based on the VNM axioms in Section 2.3.3 does not allow for such changes. Subjective decision making as discussed in Section 2.3.4 provides some flexibility in the way utility is calculated. Traditionally, the expectation of success is monotonically increasing, with the expectation of goals being successfully attained also monotonically increasing. This section introduces an alternative to existing utility functions based on changing emotional states of the agent. Since single decision making does not consider changes over time, the agent's expected utility relies on the ratio of satisfied ($|G\text{-}BR^S|$) and total ($|G\text{-}BR^{U+S}|$) goal propositions to calculate progress made and expected progress in the future.

3.5.1 Existing Expected Utility Functions

Section 2.3.4 introduced several models for calculating perceived expectation of success. Such models are meant to be human-centric and represent agents with different biases and levels of risk-taking behaviour. Noting that each model is based on monotonically increasing functions, we normalize classical theories by settling on the "expected value" function in Equation 3.18. This expected utility is a simple ratio of satisfied goals ($G\text{-}BR^S$) to all goals ($G\text{-}BR^{U+S}$), as depicted in Figure 3.4.

$$exp(t) = \frac{|G\text{-}BR_t^S|}{|G\text{-}BR_t^{U+S}|} \tag{3.18}$$

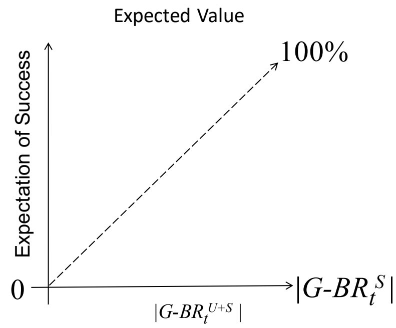


Figure 3.4: Expected value based on $exp(t)$

A key limitation of the $exp(t)$ method and its monotonically increasing characteristic is that it does not reflect how people's expectations actually change over time [39, 198, 201]. If expectation is always increasing, why do people make choices that seem to abandoned previously established beliefs without counter-beliefs? It turns out that time itself is a factor: our perception of risk, preferences, reward, or available information changes over time in a way that does not always increase expected utility.

3.5.2 Emotional Cycle Of Change and Subjective Expected Utility

In contrast to the always increasing $exp(t)$, the ECOC theory provides an expectation function that reflects the non-monotonic nature of human behaviour [125, 250], with a number of variants to reflect the true nature of human decision making [221]. Recall that ECOC theory states that individuals are overly optimistic about success and then become pessimistic once true efforts becomes apparent, and again become optimistic if sufficient gains towards completing these tasks are made. We can describe these stages in terms of increases and decreases in expectation of success. During the uninformed optimism stage, the expectation of success is high without any evidence to justify the optimism. During the pessimism stage, expectation of success falls when constraints become apparent. Finally, if constraints are removed, ECOC now resembles the $exp(t)$ function where the expectation of success again rises based on new evidence.

The $ecoc(x)$ utility function in Equation 3.19 produces the non-monotonic graph in Figure 3.5, approximating the ECOC graph in Figure 2.4. The function $ecoc(x)$ takes $exp(t)$ as its only parameter. The result is an adjusted expectation of success according to the ECOC theory,

$$ecoc(x) = \begin{cases} 0.6 - \dfrac{\sin(8x-1)+\cos(8x)}{x-2}, & \text{if } x \le 0.8\,; \\ x, & \text{otherwise}\,. \end{cases} \tag{3.19}$$

Finally, the new expected utility can be used to adjust goal utility $u(pref, s_i)$. Recall that in Section 2.3.4, subjective expected utility was calculated by multiplying the sum of all action utilities $\sum_i u(A(s_i))$ by the probability p_i of achieving proposition s_i, as per Equation 2.4. In the same way, BRAMA with single decision making combines proposition preferences $u(pref, s_i)$ with expected utility, using either

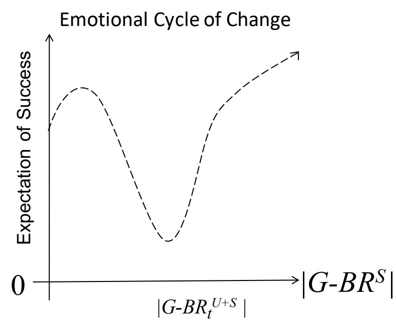


Figure 3.5: Approximation of the emotional cycle of change function with $ecoc(x)$

the $exp(t)$ or $ecoc(x)$ utility functions, as per Equations 3.20 and 3.21.

$$u(exp, pref, s_i) = u(pref, s_i) \times exp(t) \tag{3.20}$$

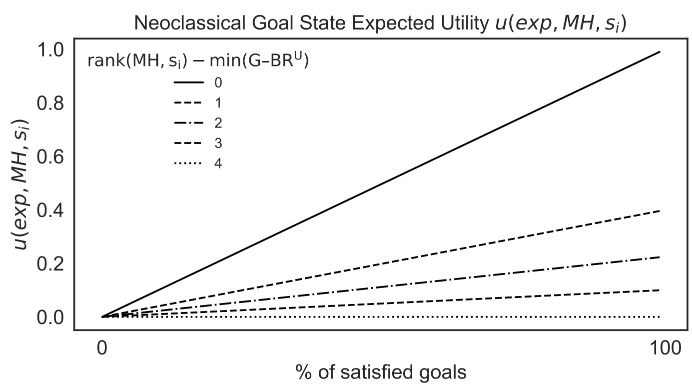


Figure 3.6: Neoclassical goal proposition utility $u(exp, pref, s_i)$ for proposition s_i at different distances between $u(pref, s_i)$ and $min(G\text{-}BR_t^U)$ as goals are being satisfied, based on $pref = MH$.

We see in Figure 3.6 that $u(pref, s_i)$ reduces the increase in utility proportionally to the difference between $rank(MH, s_i)$ and $min(G\text{-}BR^U)$. Similarly, in Figure 3.7 we see $u(pref, s_i)$ reducing the non-monotonic utility of $ecoc(x)$ from 0% to 100% of satisfied goals.

$$u(ecoc, pref, s_i) = u(pref, s_i) \times ecoc(x) \tag{3.21}$$

3.6 Discussion

To correctly emulate how a rational but bounded agent evaluates alternative choices, BRAMA identifies four factors that constrain the agent's ability to reason about goals and actions. First, for a goal-driven agent, goals must be well defined in a way that guides the agent in choosing actions. Second, actions and action characteristics available to the agent that satisfy the agent's goals must be well defined and available to the agent. Third, the agent's preferences for one goal over another must be established. Fourth, BRAMA identifies which factors constrain an agent's decision making which seems irrational to an observer.

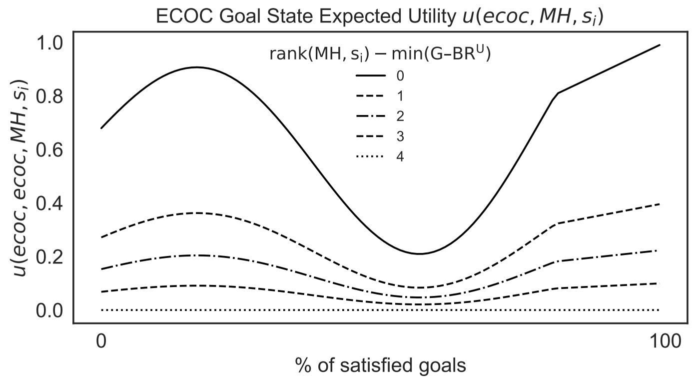


Figure 3.7: ECOC goal proposition utility $u(ecoc, pref, s_i)$ for proposition s_i at different distances between $u(pref, s_i)$ and $min(G\text{-}BR_t^U)$ as goals are being satisfied, based on $pref = MH$.

Unfortunately, the agent is constrained in a number of ways that make it seem that it is evaluating its choices irrationally. An agent's preferences change over time, adapting to limitations of the agent and external constraints. Static definitions of rational behaviour assume agents have all the information an observer thinks is needed, and any biases are well understood. While interacting with a dynamic environment, however, the agent must constantly reevaluate its decisions, making static mappings between observed actions and preferences short-lived. The BRAMA framework incorporates several theories of behaviour that highlight hidden and dynamic indicators of rationality for human-like agents.

Not all information is available to the agent, resulting in a constraint on cognitive ability to process all information that is available. Missing information manifests itself in different ways, impacting an agent's ability to rate alternative ways to satisfy its goals. Existing methods of representing and overcoming such gaps in knowledge have focused on improvements in computational efficiency, overlooking human-centric ways of adopting and overcoming such limitations. Bounded rationality provides a framework for representing gaps in knowledge and cognitive abilities. However, it does not explore how goals and actions are impacted by missing information, and how they are related. The goal semantics schema introduced here provides ways to represent the variety of relations that can exist between goals. Some goals are related out of necessity and grounded in Maslow's hierarchy, while others through common-sense or functional requirements imposed by a process or external constraints.

Finally, comparing possible courses of action towards goals relies on an agent's expectation of success. Classical behaviour theory assumes expectation is gained through experience in a rational way, with steady improvements over time. However, theories of emotions have shown how expectations change in a non-classical way. Expectations are impacted by the agent's emotional mood, moving between pessimistic and optimistic evaluations of actions. With such nonlinear changes, any theories that rely on static associations of emotions and decisions fail to capture the dynamic nature of their relationship. ECOC provides a continuously changing evaluation function of an agent's expectations, moving between optimistic and pessimistic stages based on the increasing number of achieved goals.

3.7 Conclusion

Single decision theory provides a framework for calculating the expected utility of independent choices. BRAMA provides an extension to single DT that incorporates human-centric factors for calculating expected utility. First, information and memory bounds limit a BRAMA agent from having a complete picture of available actions and underlying goals. Second, Maslow's hierarchy provides a grouping for and ordering of the initial goals used to calculate the ordinal utility of goals for individual actions. BRAMA incorporates the number of goals already satisfied and those outstanding to calculate a goal's cardinal utility. Basic semantics of goal relations were presented that assist in the mapping and grounding of goals with other goals and Maslow's hierarchy. Third, BRAMA relies on two utility functions to calculate expectations of an agent. The neoclassical expectation utility is a monotonically increasing function that assumes an agent's expectations improve over time. The emotional cycle of change provides a utility function that is non-monotonic in nature and considers an agent's emotional state.

The addition of Maslow's hierarchy and ECOC provide BRAMA with human-centric factors to calculate the utility of individual decisions. A limitation of single DT and the version of BRAMA presented so far is the assumption that the utility is calculated individually for each choice. However, choices are rarely made independently. Also, an observer who, like the agent, is bounded may not have complete information about an agent's preferences and external constraints that impact each choice the agent makes. A combined utility metric that considers more than one choice over an extended period of time may be a better approach to objectively evaluate an agent's rationality. In the next chapter, BRAMA is extended to capture a bounded observer's perspective and an agent's behaviour based on different strategies for decision making that allow for the calculation of utility for an entire sequence of actions while preferences change over time.

Chapter 4

Human-Centric Sequential Decision Making

4.1 Introduction

In this chapter the utility calculated by BRAMA is extended using dynamic choice theory (DCT). This extension increases the fidelity of the BRAMA agent model by incorporating an observer's ability to interpret the sequence of actions an agent exhibits over some period of time. The extension and increased fidelity allows the observer[1], to infer changing preferences as the agent interacts with a changing environment. To infer changing preferences, the BRAMA reasoner incorporates human-centric factors an observer would know *a priori*, in order to calculate and monitor expected utility for a given sequence. From the observer's perspective, the new utilities allow it to compare sequences of actions to determine which sequence maximizes an agent's utility, given the agent's observed behaviour and known human-centric factors that affect its choices. The relation between sequence utility and observable behaviour is stated in axiom BR-3.

In Chapter 3, behaviour was represented as independent and rational decisions based on the utility of individual actions and static choices. In a dynamic environment, a bounded agent is limited in what it knows will be the actual consequences of actions after execution. The agent is also limited in what it knows about its own response to future actions, and how its goal preferences will be affected. Similar bounds limit the observer agent from being omniscient and knowing *a priori* all factors that will impact an agent's individual decisions. To accurately emulate an agent's behaviour, then, it is more realistic to calculate a utility for the observable decisions an agent makes, and identify some recognizable pattern across a sequence of actions over time. Single decision theory is not capable of calculating and comparing the utility for the set of decisions over time, as it assumes decisions are independent of each other. Dynamic choice theory (DCT), however, provides such a theoretical framework.

A DCT model represents behaviour sequences as a decision tree, a tree-like structure where each edge is an action and each node is the starting state or a state changed by an action. Each branching node has two or more outcomes, with a condition indicating which outcome is chosen by the agent. The tree includes all "reasonable" choices the observer believes are possible for an agent to make in

[1] From now on, the observer is also considered a computational agent, but will be referred to simply as "observer" to distinguish it from the "subject" referred to as agent, as defined in Section 2.1.

order to satisfy its goals. To construct such a tree, DCT assumes the observer knows the probability of expected outcomes, and what choice an agent will choose based on one of three possible decision strategies. Subjective decision theories (SDT) provide methods for calculating such probabilities, and assume the probabilities can be calculated by the observer. Such theories assume the observer knows the state of the agent and how it will respond in a given situation. Rather than the agent, it is the environment that is uncertain, with a probabilistic representation of outcomes, given the agent's choice.

However, the observer is also not omniscient and has bounded rationality. What the observer perceives as reasonable depends on the observer's own limited understanding of the agent's knowledge and bounded rationality. Hence, agent emulation in the extended BRAMA framework is performed in two phases, one for the observer and one for the agent. The decision tree construction phase is performed by the observer and captures all sequences the observer believes a "reasonable" agent might choose. Then, during the execution phase, the agent selects and executes one of the sequences in the tree in a stepwise fashion. To be pragmatic about handling dynamic nature of future states of the world, an agent reasoning with DCT deploys a "decision strategy" that guides its reasoning process [161, 25].

Human-centric factors used to extend BRAMA impact each phase differently. During the tree construction phase the observer is limited by factors that limit the combination of actions used to construct the tree, as listed in Table 4.3. The observer is not omniscient, meaning it does not have complete knowledge about the agent or the environment, and has finite resources to construct a decision tree. The time bound limits the number of states in the search space an observer can consider while constructing the decision tree. The cognitive bound limits the depth of the paths used to construct the tree. Each path from initial node to end node the observer adds to the tree represents a sequence of actions that satisfies different permutations of goals that the observer believes the agent may pursue. Maslow's hierarchy is used to organize goals for constructing each path. If an agent chooses to follow a particular sequence, the observer assumes the permutation order used to construct that sequence is the agent's preferred initial goal order. However, not pursuing a goal does not mean the goal has been abandoned, only demoted in its preferred ranking. As Bermudez notes, expressed and observed preferences can differ due to external constraints, and expressed preferences are counterfactually retained even after becoming impossible to execute [25]. Hence the initial goal ranking may change due to constraints placed on the sequence.

During the execution phase, a BRAMA agent relies on an enhanced reasoning process that utilizes new features introduced by DCT as outlined in Tables 4.2 and 4.4. The new BRAMA agent is restricted by a time bound and cognitive bounds that limit the variety of sequences considered when calculating the utility of available choices. The agent's reliance on Maslow's hierarchy is broadened to goal utility calculation with an enhanced cardinal goal ranking, incorporating the order and distance of actions in relation to the MH levels of goals. The utility of each action and goal is calculated using Maslow's original order, representing the "true" goal order that impacts an agent's choices. As the two orders differ, the utility of each action changes, with a response controlled by the agent's decision strategy as well as its expected utility function. The neoclassical expected utility and ECOC-based utility functions are used to emulate neoclassical rational agent and emotional agents.

4.2 Extending BRAMA using Dynamic Choice Theory

In this section, the BRAMA framework introduced in Chapter 3 is extended to capture sequences of decisions made by an observer and agent. BRAMA retains the terms defined in Chapter 3 in Table

3.2 for action selection. Terms in Table 3.1 are extended in Table 4.1 to redefine BRAMA's domain representation terms for sequential decision theory. Terms in Table 3.3 are extended using bounds imposed on the observer during the tree construction phase, as per Tables 4.2 and 4.3. Bounds imposed on the agent during the decision execution phase are listed in Table 4.4. Each bound is identified with 'C' for construction-phase bounds and 'E' for execution-phase bounds.

Table 4.1: BRAMA domain representation terms for sequential decision theory

Term	**Description**
S_t	State of the world, meaning a set of propositions that are true at time t.
S	Set of states of the world, where $S_t \in S$.
s_i	Proposition with a truth assignment at some time t, where $s_i \in S_t$ means s_i is true at time step t and false otherwise.
AS	Set of available actions, where $a_m \in AS$.
A^x	Sequence of actions with a unique index x, starting at some state of the world S_t.
A^x_t	Sequence of actions with a unique index x up to and including time step t, starting at some initial state of the world S_0.
S^y_t	Subset of propositions true at time t, where $s_i \in S^y_t$ and $S^y_t \subseteq S_t$, so that $s_i \in S_t$.
action (a_m)	Action (a_m) with postcondition propositions ADD_m and DEL_m that transitions one state (S_t) to another (S_{t+1}).
a^x_k	Some action $a_m \in A^x$ at position k, meaning action a_m is the k-th action to be executed in the sequence A^x.
$exec(a_m, S_t)$	This procedure executes action a_m to transition S_t to S_{t+1}, where $exec(a_m, S_t) = S_{t+1}$, $ADD_m \subseteq S_{t+1}$, and $DEL_m \notin S_{t+1}$.
s^x_k	A true proposition after executing action a^x_{k-1} in sequence A^x, where $s^x_k \in ADD^x_{k-1}$.
O^x	The state of the world after the final action in sequence A^x, where $O^x \in S$.
PRE_m	Set of propositions that must to be true immediately before action a_m can be executed, where $PRE_m \subseteq S_t$ if a_m is executable at time step t.
$pre_{m,i}$	A proposition indexed by i that must be true for an action a_m to be executable, where $pre_{m,i} \in PRE_m$.
ADD_m	Set of propositions that need to be true immediately after action a_m has been executed, where $ADD_m \subseteq S_{t+1}$ if a_m is executed at time step t.
$add_{m,j}$	A postcondition proposition indexed by j that needs to be true immediately after action a_m is executed, where $add_{m,j} \in ADD_m$.
DEL_m	Set of propositions that need to be false immediately after action a_m has been executed, where $DEL_m \notin S_{t+1}$ if a_m is executed at time step t.
$del_{m,j}$	A postcondition proposition indexed by j that needs to be false immediately after action a_m is executed, where $del_{m,j} \notin DEL_m$.

In Table 4.1, terms are extended to represent a domain with sequential decision theory. The main difference from the previous chapter is in how consequences of executing an action are defined. Recall that in single decision theory, outcomes of alternative choices are mutually exclusive of other choices that are available or will be available in the future. In sequential decision theory, however, an action's consequences may modify and even undo the outcome of a previous actions. Hence, independence of choices is not retained. BRAMA redefines an action's outcome as "postconditions"[2], a set of propositions that can be added to but also removed from the current state of the world. For some action a_m, ADD_m

[2]The definition of postconditions as a set of added and deleted propositions is based on AI planning, which is used to extend BRAMA further in Chapter 5.

is a set of propositions that are added to S_t immediately after the action is executed, where proposition $add_{m,j} \in ADD_m$ and $ADD_m \subseteq S_{t+1}$. Also, for some action a_m, DEL_m is a set of propositions that are deleted from S_t, where proposition $del_{m,j} \in ADD_m$ and $\varnothing = DEL_m \cap S_{t+1}$.

Table 4.2: BRAMA sequence utility terms for sequential decision theory

Term	**Description**
Decision Strategy	Strategy used by an agent's reasoner that selects a branch in the decision tree: myopic, sophisticated, or resolute.
Condition Function ($C_{ds}(x,t)$)	Condition for selecting a branch x at time step t in the decision tree, associated with each decision strategy ds, where $ds \in \{m,s,r\}$ for myopic, sophisticated, and resolute, as per Equations 4.10 to 4.13.
$execu$	Label to indicate which expected utility function is used to calculate utility of actions and sequences, where $execu \in \{exp, ecoc\}$ for neoclassical function $exp(t)$ and ECOC-based function $ecoc(x)$, as per Equations 4.8 and 4.8 respectively.
$U(execu, pref, A^x)$	Expected utility for sequence A^x, where $execu \in \{exp, ecoc\}$ indicates utility functions $exp(t)$ or $ecoc(x)$ as defined in Equations 4.6 and 4.7 respectively.
aw^x_k	Weight assigned to the k-th action in sequence A^x based on the distance of any add-proposition $add^x_{k,i} \in ADD^x_k$ and an MH goal proposition in A^x, where $aw^x_k \in [0,1]$, as per Equation 4.5.
po^x_k	Weight assigned to the k-th action in sequence A^x based on whether it satisfies an unsatisfied goal, where $po^x_{k,i} \in \{0,1\}$.
$pref$	The ordering for a set of goals, where $pref \in \{A, MH, x\}$ for the agent's preferred order, Maslow's order, and practical order after execution of sequence A^x and outcome O^x.
$u(pref, s_i)$	Cardinal utility of action a^x_t where $s_i \in ADD^x_t$ and $pref$ is some ordering, as per Equation 3.17.
$u(execu, pref, a^x_k)$	Expected utility function for action a^x_k, where $execu \in \{exp, ecoc\}$ and $pref$ is some ordering, as per Equations 3.20 and 3.21.
$U(execu, pref, a^x_k)$	Expected utility function for action a^x_k in sequence A^x relative to goal propositions it satisfies in $G\text{-}BR^U_t$, where $execu \in \{exp, ecoc\}$ and $pref$ is some ordering as per Equations 4.6 and 4.7.

BRAMA agents extended by DCT calculate utility according to the decision strategy employed by the agent. For each decision strategy, the agent calculates the utility of each choice using different conditions $C(x,t)_{ds}$ as defined by Equations 4.10 to 4.13. The myopic strategy where $ds = m$ only considers the utility of actions available at the current time step t, recalculating the utility at each new time step. This strategy is similar to single DT in that immediate actions are independent from actions at other time steps. The sophisticated strategy where $ds = s$ also recalculates utility at each time step, but considers the entire sequence of actions to choose the best action. This strategy chooses the sequence for which the utility of the entire sequence is closest to the utility of its immediate action. Finally, the resolute strategy where $ds = r$ calculates sequence utility only at the beginning (at $t = 0$). The sequence with the maximum utility calculated at time step $t = 0$ is executed until the end without recalculating utility.

The agent's reliance on Maslow's hierarchy is also broadened to extend goal utility calculation with an enhanced cardinal goal ranking. The enhanced ranking considers not just the number of goals, but also the order in which MH level goals are satisfied in the sequence. The new cardinal utility is combined with neoclassical and emotional expected utility to emulate behaviour of emotional and non-emotional agents over an extended period of time.

Table 4.3: BRAMA observer terms during the construction phase

Term	**Description**
$S\text{-}C$	State of the world the observer knows about.
$G\text{-}C$	Set of goal propositions the observer believes the agent should want to be true.
$AS\text{-}C$	Actions the observer knows about and is aware of within its information and cognitive bounds. This is a combination of correct and incorrect knowledge about actions, where $AS\text{-}C \subseteq AS\text{-}cor \cup AS\text{-}inc$.
$BR\text{-}C(I)$	Information captured by the observer's limited knowledge, where $BR\text{-}C(I) = \{S\text{-}C, G\text{-}C, AS\text{-}C\}$.
$BR\text{-}C(C)$	Cognitive bound during the construction phase limiting an observer's decision tree depth, where $BR\text{-}C(C) \in \mathbb{Z}$.
$BR\text{-}C(T)$	Time bound during the decision tree construction phase limiting the number of states in the search space used to construct the tree, where $BR\text{-}C(T) \in \mathbb{Z}$.
$rank(x, s_i)$	Preference ranking for goal proposition s_i associated with some sequence A^x, where $s_i \in G\text{-}C$.

During the tree construction phase, sequence utility is not used to build a path in the tree. Instead, the add-proposition of each action is used as the heuristic that guides the sequence towards satisfying goals, along with supplementary factors described in Table 4.3. The goal order is a secondary heuristic to prioritize goals for action selection in a meaningful and practical way. To construct the tree, a bounded, greedy forward-search algorithm is used to build each path in the tree within the bounds of the observer. The search heuristic expands the tree on nodes that reduce the number of goals outstanding in $G\text{-}BR^U_t$. The depth of each path is bounded by $BR\text{-}C(C)$. The action definitions and goals the observer has available to it are based on $BR\text{-}C(I)$ and the order of initial goals based on goal ranking *pref* at time step $t = 0$. Since the observer may not know in what order the agent prefers goals, the observer will include sequences that satisfy different permutations of goal orders, where each permutation is labelled by the *pref* parameter. Each permutation is then associated with a sequence outcome, where outcome O^x is associated with the initial goal order. These initial goals are grouped by their Maslow levels in different permutations, to be discussed in Section 4.3. However, they are not necessarily in Maslow's order. For example, all physiological goals are grouped together but are not necessarily ranked higher than social goals. The ranking will be based on which *pref* is used.

Since an agent's behaviour is evaluated from the perspective of the observer, all aspects of an agent's decision making are limited to what the observer believes influences the agent's choices. During the execution phase, a BRAMA agent relies on an enhanced reasoning process that utilizes new features outlined in Tables 4.1 and 4.4. The extended BRAMA agent is also bounded by knowledge and memory limitations. With the introduction of the time dimension representing sequences of actions, the agent is limited by the time bound, $BR\text{-}E(T)$. The time bound limits the number of states in the search space an agent can consider while calculating the utility of available choices. $BR\text{-}E(I)$ is the limited knowledge available to the agent during decision making. Since the agent follows sequences in the decision tree constructed by the observer, the agent is limited to knowing a subset of the observer's knowledge in $BR\text{-}C(I)$. Along with time, the complexity of reasoning about goals must also be considered, as multiple sequences can be generated to satisfy the same goals. Hence, a BRAMA agent's cognition is also limited by $BR\text{-}E(C)$, the cognitive bound limiting the length of sequences considered when calculating the

Table 4.4: BRAMA agent terms during the execution phase

Term	Description
$S\text{-}BR$	State of the world the observer believes the agent knows about, where some subset of propositions true in S_t are true in $S\text{-}BR$.
$G\text{-}BR$	A set of goal propositions the observer believes an agent wants to be true.
$AS\text{-}BR$	Actions the observer believes the agent knows about within its information and cognitive bounds. Assuming the observer is aware of all possible actions and goals an agent knows about, it is the case that $AS\text{-}BR \subseteq AS\text{-}C$
$BR\text{-}E(I)$	The agent's limited knowledge according to the observer, where $BR\text{-}E(I) = \{S\text{-}BR, G\text{-}BR, AS\text{-}BR\}$.
$BR\text{-}E(C)$	Cognitive bound limiting the depth of an agent's decision tree, where $BR\text{-}E(C) \in \mathbb{Z}$ and $BR\text{-}E(C) < BR\text{-}C(C)$, indicating an agent's bound is lower than the observer's.
$BR\text{-}E(T)$	Time bound during the execution phase limiting the number of states on the search space used to calculate utility, where $BR\text{-}E(T) \in \mathbb{Z}$ and $BR\text{-}E(T) < BR\text{-}C(T)$, indicating an agent's bound is lower than the observer's.

utility of available choices.

4.3 Decision Tree Construction Phase

The decision tree represents a set of decision sequences the observer believes an agent may follow. Since the observer is also bounded, it does not know certain information about the agent. For example, the observer does not know the agent's preferred order at the beginning of the sequence, hence it must use different goal orders and construct a tree for each one. The BRAMA observer relies on the goal-ordering heuristic described in Section 4.3.2. First, the observer organizes goals by their MH level into five separate groups. It then generates all permutations of the groups. Knowing that certain goals are abandoned, each permutation has an additional goal order that removes the last MH group in the permutation, as discussed in Section 4.3.2. Once all permutations are generated, the path construction heuristic creates a sequence for each permutation, as described in Section 4.3.3. The algorithm uses a greedy forward-search heuristic to find the first *possible* action sequence that satisfies all goals in the permutation. A *possible* sequence is one in which all action preconditions are true before the action is added to the sequence. Due to the preconditions, actions do not necessarily satisfy goals in the initial order. Hence, an agent with an initial preferred order where $rank(pref, s_i)$ at time step $t = 0$, and $pref = A$ for agent, may finish the sequence satisfying goals in a different order. The order of goals after execution has completed is referred to as the "practical" order for some sequence A^x, where $pref = x$ indicates that the goal order is the same order goals were satisfied in by sequence A^x.

4.3.1 Bounded Observer

The need for grouping and generating permutations is due to the bounds placed on the observer and preconditions placed on the actions. Without a bounded observer or constrained actions, a simple enumeration of all possible actions and goals would be sufficient to construct a decision tree. Consider a simple representation with a one-to-one relation between actions and goals, where action a_i satisfies goal proposition s_i. The number of action permutations is then equal to the number of paths in the decision tree. Without a time or cognitive bound, all paths can be evaluated by the observer and compared to the observed actions of an agent. Consider an agent with only 10 goals, where the observer does not know the agent's preferred order and must then construct a decision tree that will match all possible permutations of actions an agent can follow. Such a decision tree would require $10! = 3,628,800$ paths to capture a sequence for each possible permutation of the agent. Taking a naive approach to tree construction would produce a large tree.

Assuming the observer is bounded, a more realistic and efficient approach to constructing a tree is needed. Such an approach would ignore branches with an impossible or unlikely order of actions and goals based on information about the target domain. For example, consider again the social service agent introduced in Section 3.4.1 with mappings in Figure 3.2. Three of its goals are: not being hungry (physiological), having housing (security), and spending time with friends (social). The actions available to satisfy these goals are ones the observer believes are available to the agent, where $AS\text{-}BR \subseteq AS\text{-}C$. These include going to the soup kitchen to obtain a hot meal, visiting a housing worker to help with securing housing, and going to the shelter's common area to socialize. Functional constraints must be considered to realistically execute a sequence of actions that satisfies all three goals.

Imagine that all three goals can be achieved at the same shelter but with some preconditions. Hot meals are served at 11:00 am and 12:00 pm. The agent's friends only arrive at 12:00 pm, afterwards going to the common area for the remainder of the day. The agent can book an appointment with a housing worker but must stay in the waiting area without leaving until its number is called. Due to a high demand, this can take up the entire day, longer than its friends are willing to stay at the shelter to socialize. The agent is worried that once it meets its friends, it may be tempted to stay in the common area and risk not meeting with a housing worker. Three possible sequences are illustrated in Figure 4.1.

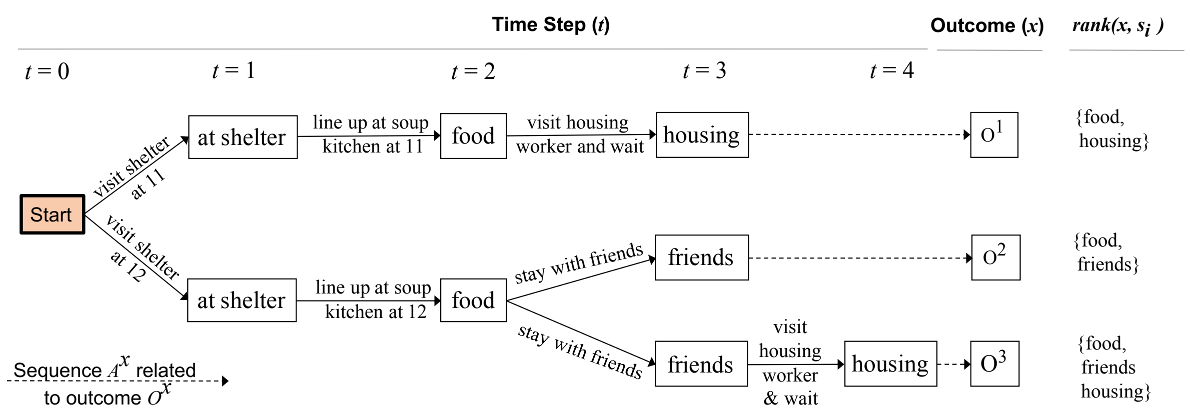


Figure 4.1: Homeless agent decision tree example

Each sequence leads to different goals being satisfied in a different order. Outcome O^1 associated with sequence A^1 satisfies food and housing at time step $t = 3$, with $pref = 1$ indicating the practical order of sequence A^1. Outcome O^2 satisfies food and friends also at time step $t = 3$ with $pref = 2$ for sequence A^2. Outcome O^3 satisfies food, friends, and housing with $pref = 3$, but sequence A^3 takes an extra time step compared to A^1 and A^2, finishing at time step $t = 4$. During the execution phase, the agent can choose which sequence to follow.

The algorithm BRAMA uses to create each sequence in a decision tree is a greedy heuristic search with a dynamic MH-based goal ordering. The greedy bounded heuristic algorithm relies on some method that selects the most likely node to satisfy goals. It then expands on that node and applies the heuristic again. The BRAMA heuristic performs a means-end analysis and relies on the precondition propositions and add-propositions of each action as well as the initial goal order [231, 83]. The remainder of this section introduces the goal ordering and tree construction heuristics utilized by BRAMA.

4.3.2 Goal Ordering Heuristic

In the homeless agent scenario presented in Figure 4.1, three goal orderings were chosen to construct three paths in the decision tree. This section describes how each permutation for the initial goal ordering at times step $t = 0$ for each path x is chosen.

Maslow's Hierarchy

During the tree construction phase, using all permutations of goals to construct paths may be too large, and the $BR\text{-}C(T)$ limit can easily be reached before considering a sufficient variety of goal orderings. As mentioned in Section 4.3.1 it only requires 10 goals to produce $3,628,800$ permutations of goal orderings. An average path depth of 10 would require $BR\text{-}C(T)$ to be around $7,257,600$. Instead, BRAMA relies on Maslow's hierarchy to reduce the number of paths constructed. Rather than iterating through all permutations of individual goals, the goals are combined into groups by their MH level. "Reasonable" permutations of goal groups are then selected, as discussed in the next section. With five MH-levels, the number of permutations now has an upper bound of $5! = 120$ groups, producing 120 paths. The upper time bound for constructing a tree with an average depth of 10 is now 240, a more reasonable limit.

Selecting Reasonable Goals

The selection of goal permutations an agent might think are "reasonable" is not straightforward. In DCT, preferences are dynamic, changing from one time step to the next. In some instances, one goal replaces another, removing the replaced goal completely. In other cases, preferences can be expressed counterfactually, where outcomes with unattainable goals do not disappear from the preferred outcome list. Instead, the agent's outcome preferences are reordered, reducing the rank of unattainable outcomes [25]. In Figure 4.1, outcome O^1 drops the "friends" goal, indicating social needs are not as important as food and housing. In outcome O^2, the "housing" goal is dropped, indicating security needs are least important. In outcome O^3, all goals are satisfied, indicating the agent was committed to satisfying all of its goals.

This short example demonstrates that different permutations of goals are required to capture possible orders of action sequences an agent may have. An exhaustive search of all possible action permutations could be used to match any goal permutation. However, due to the observer's own time bound, a limited number of goal permutations must be provided for which the algorithm can choose the most appropriate action sequence. Hence, BRAMA relies on a simple algorithm for different permutations of MH levels to produce permutations of goals illustrated in Figure 4.2.

The homeless agent example includes three levels: physiological, security, and social. Since goals can be removed, as demonstrated in outcomes O^1 and O^2, the permutations will include n and $n-1$ MH levels, where n is the total number of levels an agent has goals for (e.g. $phys, sec, soc$). The case where $n-1$ levels are kept means goals in the least preferred level are dropped. The final permutations with $n = 3$ result in $2 \times 3! = 12$ variations of $rank(x, s_i)$, where $x \in \{1, \ldots, 12\}$. These permutations are used

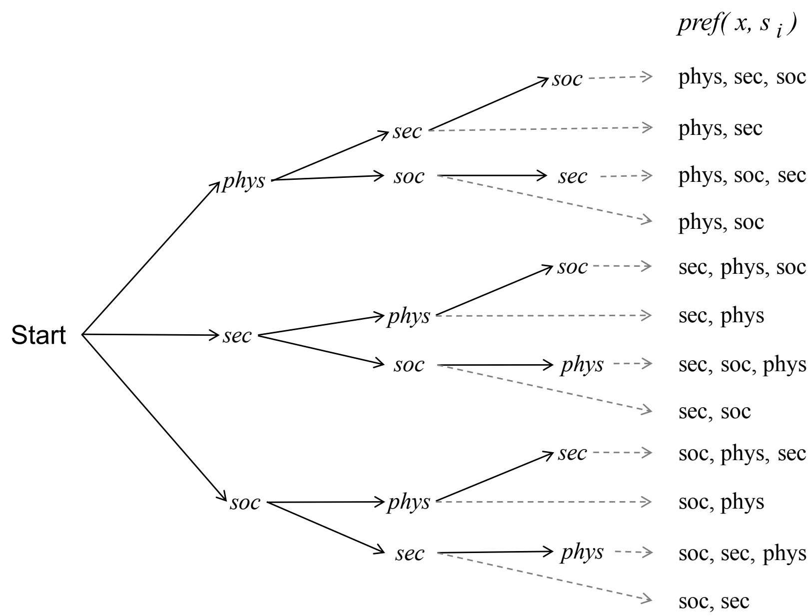


Figure 4.2: Permutations of MH-level goal groups x where $phys$, sec, and soc represent physiological, security, and social needs

to initialize the construction of the path representing sequence A^x, as per Figure 4.2.

4.3.3 Path Construction Heuristic

For each goal order permutation, BRAMA constructs separate sequences that are added to the main decision tree. Each sequence is created using a greedy, forward heuristic search algorithm. The algorithm expands a path based on the action edge that reduces the difference between $G\text{-}BR$ and $S\text{-}BR_t$ in a procedure called means-end analysis [231]. Path expansion continues until a sequence is found that satisfies all goals, where $G\text{-}BR \subseteq S\text{-}BR_t$. The heuristic used by BRAMA is to expand on actions that satisfy existing goals according to the order of unsatisfied goals in $G\text{-}BR_t^U$ at time step t. When an action that satisfies a goal has unsatisfied preconditions, those preconditions are added to the beginning of the goal list and an action is found to satisfy the added goals. The algorithm is presented in Figure 4.3.

In the decision tree example in Figure 4.1, there are two actions for obtaining food, "soup kitchen at 11" and "soup kitchen at 12." Each one has a precondition of being at the shelter and that the current time of day be either 11 am or 12 pm. The action's add-proposition is that of providing food. The action of "visit housing worker" has a precondition for the agent to be at the housing worker's office early enough to book an appointment and then to wait, and add-propositions that satisfy some precondition of having housing, such as "be with housing worker" and "receive housing listings". The preconditions for staying with friends may include "being at the soup kitchen at noon" and "visiting the common area". An add-proposition for being with friends might be "socializing with friends." A delete-proposition would remove any previously true propositions from S_t that are no longer true in S_{t+1}, such as "be with housing worker" once the agent has left the housing worker's office.

This tree construction algorithm performs a separate search for each permutation. For example, given

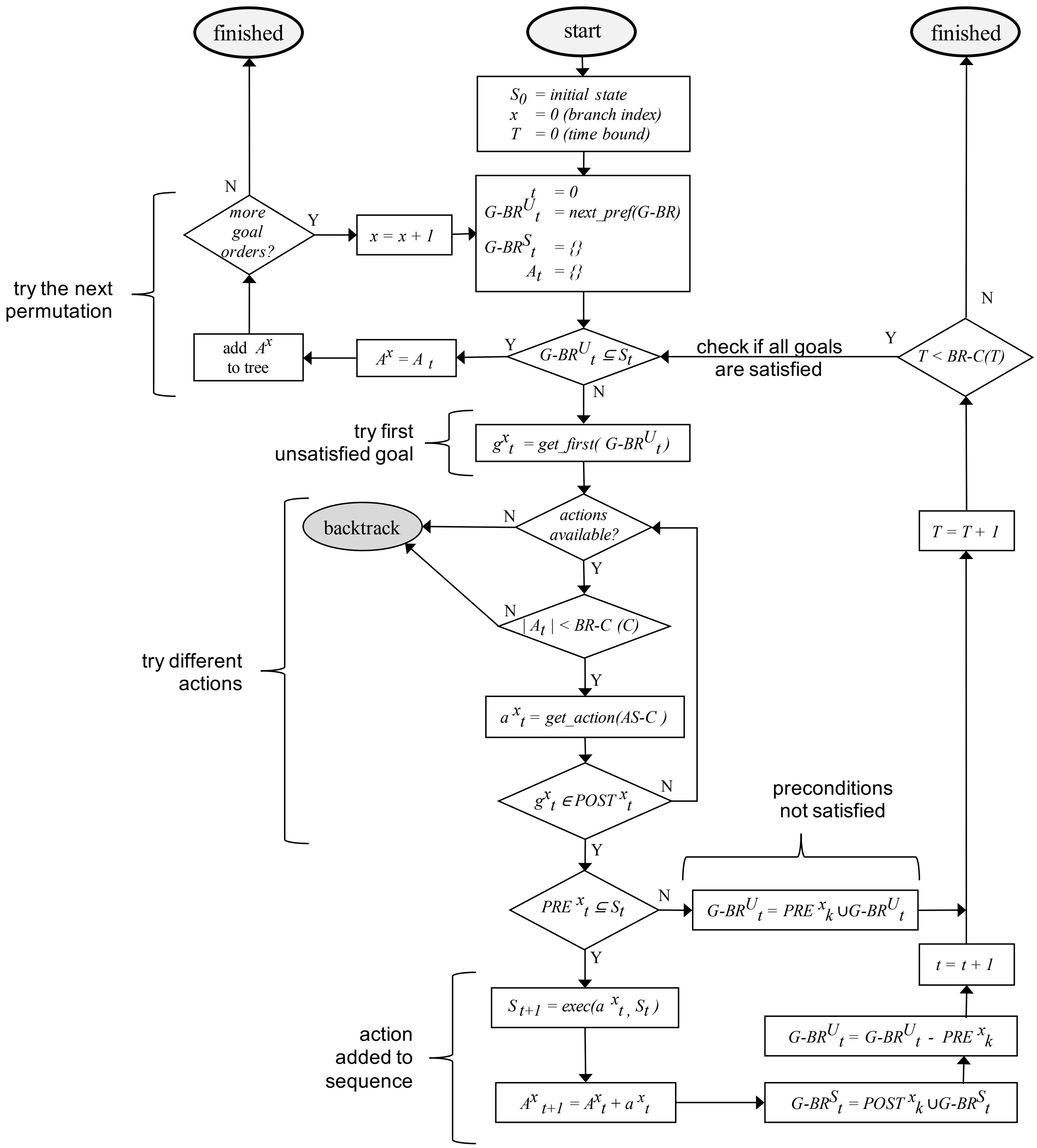


Figure 4.3: Decision tree construction algorithm

the initial preferred goal permutation $rank(x, s_i)$ where $G\text{-}BR_0^U = \{food, housing, friends\}$, the first action to search for is one that satisfies the $food$ goal. Say the action is to "get food at the soup kitchen at 11" as per action $a_m = get(food, soup\_kitchen\_at\_11)$. This action has a precondition of the agent being at the shelter by 11 am, where $PRE_m = \{at(A, soup\_kitchen\_at\_11)\}$. This goal proposition, an interim goal, is added to $G\text{-}BR_t^U$ producing $G\text{-}BR_t^U = \{at(A, soup\_kitchen\_at\_11), food, housing, friends\}$. The newly added interim goal is now the highest-ranked unsatisfied goal. A new action search is performed to find an action that satisfies this interim goal. This process continues until an action is found that has no unsatisfied preconditions. When this action is found, it is executable, satisfying the first goal proposition in $G\text{-}BR_t^U$, and the time step t is increased by one. The goals of executable actions are removed from $G\text{-}BR_t^U$ and added to $G\text{-}BR_t^S$ at time step t. This precondition satisfaction process is repeated until all goals in $G\text{-}BR_t^U$ are satisfied, meaning when $G\text{-}BR_t^U \subseteq S_t$.

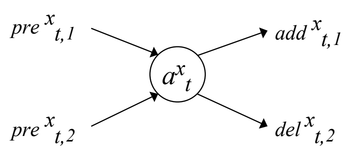


Figure 4.4: Action a_t^x with preconditions ($pre_{t,i}^x$) and postconditions ($add_{t,j}^x$ and $del_{t,k}^x$)

The heuristic for selecting an action and adding it to sequence A^x at time step t as a_t^x requires that actions are defined with preconditions PRE_t^x, where $pre_{t,i}^x \in PRE_t^x$, and postconditions ADD_t^x and DEL_t^x, as per Figure 4.4. The algorithm chooses the first unsatisfied goal proposition $s_i \in G\text{-}BR_t^U$ and selects an action that satisfies that proposition, where $s_i \subseteq ADD_t^x$. Next, if the action's preconditions are true, where $PRE_t^x \subseteq S_t$, the action is added to the sequence A^x, assigned the label a_t^x from a_m, and the next goal on the list is selected. If the action's precondition propositions are not true they are added to the beginning of $G\text{-}BR_t^U$ in the same way that they are defined in the precondition set PRE_t^x. New actions are then selected that satisfy the newly added goal propositions. The process continues until all goal propositions are satisfied, where $G\text{-}BR_t^S \subseteq S\text{-}BR_t$.

The depth of expansion is limited by the cognitive bound $BR\text{-}C(C)$. If a sequence is not found within that limit the algorithm backtracks and tries a different action to expand on. Backtracking prevents partial sequences, those that satisfy a partial set of goals in $G\text{-}BR^U$, from being constructed. Once the first sequence that satisfied all goal propositions is found, that sequence is added to the decision tree. If no such sequence is found, the tree construction algorithm returns an error and the program halts. This process is repeated for each permutation of goal rankings $rank(pref, s_i)$ chosen by the observer.

4.4 Execution Phase

Unlike single DT, sequential DT makes a distinction between constructing available choices and executing them at a future time. By separating these two phases, it is possible that the state of the world and agent preferences have changed by the time the sequences are to be executed. During execution, the decision tree represents a set of action sequences the agent can choose from within its own reasoning bounds. The focus of this section is to determine how an agent decides which sequence to choose and why.

4.4.1 Action Utility Calculation based on Maslow's Hierarchy

Maslow's hierarchy contributes to the calculation of goals by associating actions with the utility of goals. Actions that contribute directly to an MH goal have a higher score than interim actions. Any sequence that satisfies lower and more important MH-level goals is assigned a higher utility.

To calculate whether an action should be active, meaning it satisfies outstanding goal propositions at time step t in sequence A^x, the activation weight po_t^x is defined, as per Equation 4.1. Recall from Section 4.3.3 that an action can have more than one add-proposition, each indexed by i for some time step t, as per $add_{t,i}^x$. If at least one goal proposition s_i is satisfied by some add-proposition $add_{t,i}^x$ at time step t the action is activated, and its activation weight po_t^x is set to 1. If no goal proposition s_i is satisfied by the postcondition at time step t the action is deactivated by setting po_t^x to 0.

$$po_t^x = \begin{cases} 1, & add_{t,i}^x \subseteq G\text{-}BR_t^U\,; \\ 0, & \text{otherwise}\,. \end{cases} \tag{4.1}$$

Once activated, the action's utility can be calculated based on the MH-levels of goal propositions it satisfies. Here, BRAMA incorporates the $u(MH, s_i)$ utility defined in Equation 3.17 in Section 3.4.2. Recall that $u(MH, s_i)$ is based on the MH level of s_i in relation to the lowest-ranked outstanding MH-level goal proposition. This ensures that, for example, esteem-level goal propositions are ranked lower if physiological-level goals are still outstanding.

4.4.2 Neoclassical and Emotional Expected Utility

By extending BRAMA using sequential DT, goal proposition utility using neoclassical and emotional utility functions $u(exp, pref, s_i)$ and $u(ecoc, pref, s_i)$ in Equations 3.20 and 3.21 are used to calculate action utility. The new Equations 4.2 and 4.3 incorporate the newly introduced action weights. Relying only on single DT to calculate utility, all actions contribute equally to each MH goal. An action may have had a high probability of expected success but contribute very little to more important goals. Since both $u(exp, pref, s_i)$ and $u(ecoc, pref, s_i)$ tell us how much action a_k^x contributes to an agent's highly ranked MH goal propositions, they are used to assign weight to the action's utility. If the neoclassical expected utility function $exp(t)$ is used, action utility is calculated with $u(exp, pref, s_i)$ in Equation 4.2, while $u(ecoc, pref, s_i)$ in Equation 4.3 uses the ECOC function $ecoc(x)$.

As Figure 4.5 shows, $u(exp, pref, s_i)$ reduces an action's utility $u(exp, pref, a_t^x)$ proportionally to its goal proposition's distance from the lowest MH level. Here, as goals are being satisfied from 0% to 100%, the overall utility $u(exp, pref, a_t^x)$ increases as is characteristic of the neoclassical function $exp(t)$. However, the increase is reduced relative to the lowest unsatisfied goal proposition in $G\text{-}BR_t^U$ at time step t.

$$u(exp, pref, a_k^x) = \frac{\sum\limits_{add_{k,i}^x \in ADD_k^x} \left(po_{k,i}^x \times u(exp, pref, s_i)\right)}{|ADD_k^x|} \times exp(t) \tag{4.2}$$

Similarly, the ECOC utility function is reduced, as per Figure 4.6 for equation $u(ecoc, pref, a_t^x)$. Here, as goals are being satisfied from 0% to 100%, the overall utility moves through optimistic and pessimistic stages as is characteristic of the $ecoc(x)$ function. However, the overall action utility $u(ecoc, pref, a_t^x)$ is reduced relative to the action's add-propositions and lowest MH level of unsatisfied goal propositions.

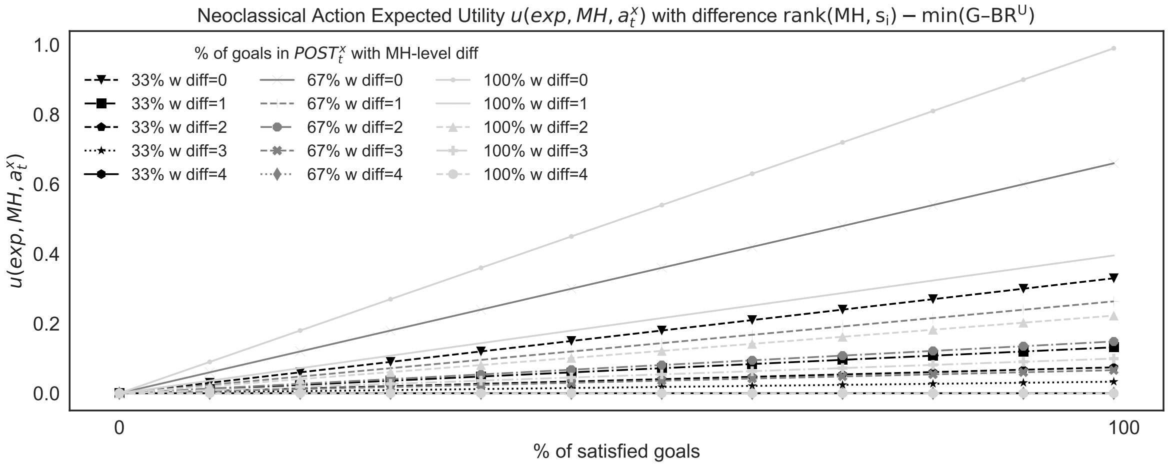


Figure 4.5: Neoclassical action utility $u(exp, pref, a_t^x)$ for action a in sequence A^x at different distances between $rank(pref, s_i)$ and $min(G\text{-}BR_t^U)$ as goals are being satisfied, with $pref = MH$.

$$u(ecoc, pref, a_k^x) = \frac{\sum_{add_{k,i}^x} \left(po_{k,i}^x \times u(ecoc, pref, s_i)\right)}{|ADD_k^x|} \times ecoc(x) \tag{4.3}$$

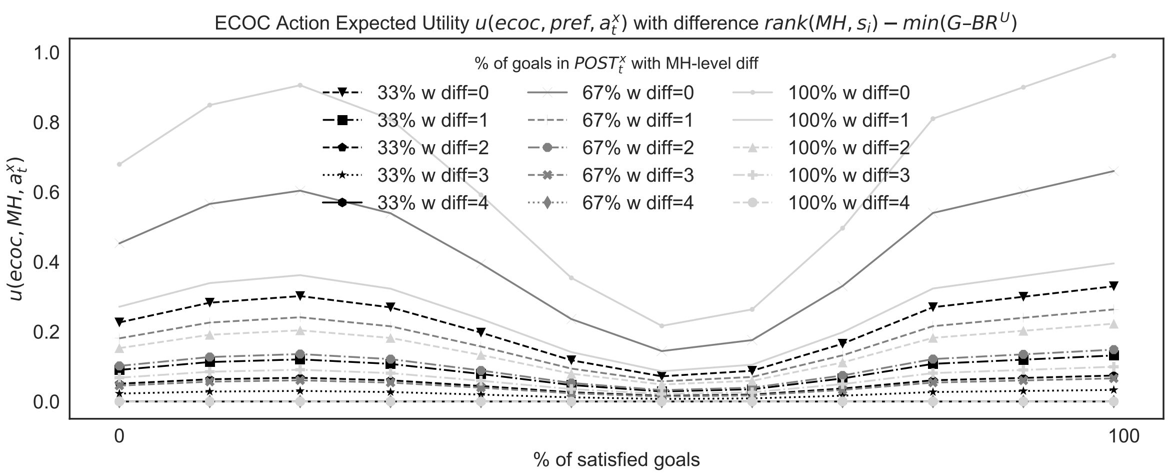


Figure 4.6: ECOC action utility $u(ecoc, pref, a_t^x)$ for action a in sequence A^x at different distances between $rank(pref, s_i)$ and $min(G\text{-}BR_t^U)$ as goals are being satisfied, with $pref = MH$.

4.4.3 Sequence Expected Utility

By combining goal and action utilities presented so far, an agent relying on either the sophisticated or resolute strategy will ultimately calculate the utility for the sequence before making a decision. In this section, the final calculation for the expected utility of a sequence is presented. Here, an action is evaluated not just against the utility of a goal, but in terms of the action's contribution to a goal relative to its position in the sequence.

Relative Expected Utility of Actions

The calculation of an action's expected utility is based on the probability of successfully achieving a goal that action satisfies. Similarly to the planning horizon problem where the reliability of information about inventory continuously deteriorates, in BRAMA those goals that can be achieved closer to the current time step have a higher probability of having been accurately assessed earlier [196]. Hence, the probability of success depends on the action's position in the plan. Also, it is possible that one action can satisfy goals at different time steps of a plan. This scenario occurs when alternative actions, as defined in Equation 3.9 in Section 3.3.2, exist in the same sequence but at different time steps.

For example, imagine that a shelter offers two types of takeaway meals, a hot meal or sandwiches. The agent is free to eat the hot meal first with the action "eat hot meal" and the sandwiches later in the day with the action "eat sandwich," and vice versa. Say the agent is hungry now and executes the action "eat hot meal" that has a precondition "have food" (which is true) and the add-proposition "not hungry" is an unsatisfied goal in $G\text{-}BR^U$. The action "eat sandwich" has the same precondition and add-proposition. If the agent becomes hungry again later in the day, say after executing the action "walk to park" which makes the agent hungry, the goal "not hungry" is added again to $G\text{-}BR^U$. The agent can now execute the action "eat sandwich" since its precondition "have food" is true and it satisfies the goal "not hungry." The fact that both actions can be executed earlier and later in the sequence, specifically before and after the action "walk to the park," increases their utility in the sequence A^x. This scenario assumes that being at the park is a highly ranked goal and that is worth performing the extra actions involved in having two meals.

Generally speaking, if an action a_t^x originally at time step t in sequence A^x can be executed at some other time steps k, the action's utility increases. For each basic goal s_i^x, there is a subsequence $A_t^x(s_i^x)$ of actions required to satisfy goal s_i^x from the sequence's initial state S_0. First, to calculate the distance between an arbitrary state S_t and some goal $s_{m,i}^x \in ADD_{m,i}^x$ satisfied by action a_m^x in sequence A^x,

$$dist(S_t, s_{m,i}^x) = \text{number of actions between } S_t \text{ and action } a_m^x \tag{4.4}$$

returns the number of actions required to transition from state S_t to a state when goal proposition $s_{k,i}^x$ is true. Second, the weight

$$aw_k^x = 1 - \frac{dist(S_t, s_{k,i}^x)}{dist(S_0, s_{n,j}^x)} \text{ where } k < n, \tag{4.5}$$

relies on this distance to calculate the contribution that action a_k^x makes to sequence A^x. Here, $dist(S_t, s_{k,i}^x)$ is divided by $dist(S_0, s_{n,j}^x)$, the distance between the sequence's initial state S_0 and when some goal proposition $s_{n,j}^x$ is satisfied by some action $a_{n,j}^x$. Here, $m < n$ ensures that the weight is being calculated for an action earlier in the sequence relative to an action later in the sequence. A higher weight aw_k^x means action a_k^x is closer to the target goal $s_{n,j}^x$ in sequence A^x, and contributes more to the sequence's overall utility, as defined below, than actions earlier in the sequence.

Finally, $U(execu, pref, a_t^x)$ calculates the contribution action a_t^x makes to the entire sequence x for all goal propositions s_i satisfied in the sequence, as defined in Equations 4.6 and 4.7 for neoclassical and ECOC-based utilities.

$$U(exp, pref, a_m) = u(exp, pref, a_m) \times \sum_k aw_k^x \tag{4.6}$$

$$U(ecoc, pref, a_m) = u(ecoc, pref, a_m) \times \sum_k aw_k^x \tag{4.7}$$

Each function takes on the characteristics of the utility function being used, as compared in Figure 4.7. The neoclassical function retains the familiar non-monotonic rising pattern of $exp(t)$. The ECOC-based function retains the optimistic and pessimistic stages of the ECOC graph.

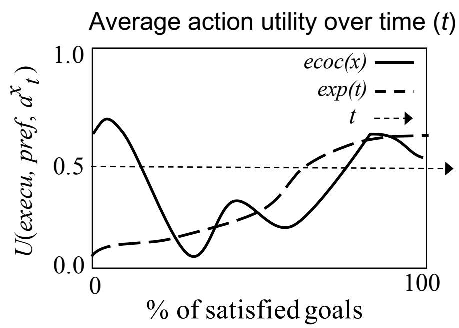


Figure 4.7: Comparison of average action utility $U(execu, pref, a_t^x)$ for action a at various times steps t as goals are being satisfied in sequence A^x for neoclassical ($exp(t)$) and ECOC-based ($ecoc(x)$) utility functions

Sequence Utility

Up to this point, this chapter has defined what contributes to the utility of goals and actions. As discussed in Section 4.1, the observer can infer factors impacting a subject's behaviour by comparing entire sequences rather than individual actions. Hence, it is important to understand how each expected utility and preferred ranking influences the utility of the entire sequence over time. In this final section the utility of a sequence is calculated based on the utilities of goals it satisfies and actions it encompasses. The sequence expected utilities $U(exp, pref, A^x)$ and $U(ecoc, pref, A^x)$ are calculated as the mean utility of all actions in sequence A^x, as per Equations 4.8 and 4.9.

$$U(exp, pref, A_t^x) = \frac{\sum_k U(exp, pref, a_k^x)}{|A_t^x|} \tag{4.8}$$

$$U(ecoc, pref, A_t^x) = \frac{\sum_k U(ecoc, pref, a_k^x)}{|A_t^x|} \tag{4.9}$$

As the individual actions are executed, the characteristics of the expected utility being used are again retained, but averaged out over the entire sequence, as illustrated in Figure 4.8. The neoclassical function characteristically rises for most of the sequence. The ECOC-based function rises at first to an optimistic stage, then drops and remains at a pessimistic stage, before finishing at an optimistic phase.

A rational agent now has the ability to select a sequence from the decision tree that maximizes expected utility, using either a neoclassical or ECOC-based utility and preferred MH mapping and ranking. The observer can now observe the sequence selected as it is executed by the agent. Based on the outcome O^x for sequence A_0^x starting at time step $t = 0$, the observer can attempt to infer which goals the agent preferred after execution, as per the new axiom BR-3:

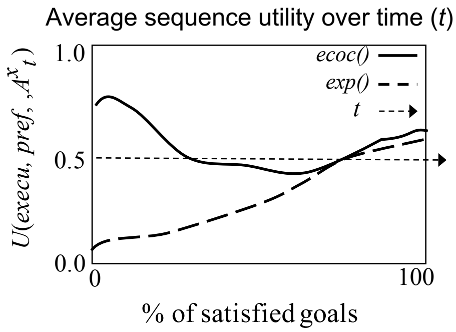


Figure 4.8: Average sequence utility $U(execu, pref, A^x)$ for sequence A^x for neoclassical utility ($exp(t)$) with $pref = A$ and ECOC-based utility ($ecoc(x)$) with $pref = MH$.

Axiom BR-3 (Sequence utility for MH order is equivalent to outcome preference)

$$U(A_0^x) \geq U(A_0^y) \iff O^x \succ_{MH} O^y \tag{BR-3}$$

The conclusion of this axiom is important. The axiom shows how an observer can infer goal preferences from behaviour modelled by subjective decision theory, but breaks one of Savage's axioms in subjective decision theory introduced in Section 2.3.4. We know that the outcome is observable. The factors used to calculate sequence utility are either observable or can be enumerated and matched to one of the three decision strategies. However, this axiom breaks Savage's fourth axiom, which requires the outcome to be independent of sequence utility. As calculations for sequence utility have shown, such independence between sequence utility and outcome preference unnecessarily hides the agent's goal preferences from the observer.

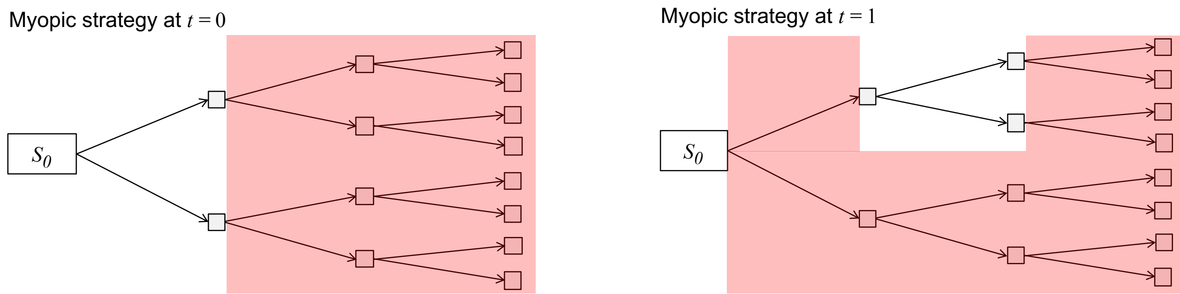
4.4.4 Decision Strategies

According to dynamic choice theory, during the execution phase the agent may use one of several decision strategies to choose an action, where each strategy has a unique utility function [104, 161, 25]. Some strategies recalculate utility at each step, some consider past experiences, while others only future ones. For example, the myopic strategy treats each choice as being independent from others, while the resolute strategy considers the entire sequence as a whole. The sophisticated strategy only considers future actions but compares them to the utility of immediate actions. Each strategy has a unique decision condition $C_{ds}(x, t)$ that captures their respective utility calculations, where $ds \in \{m, s, r\}$ for myopic, sophisticated, and resolute. These conditions are defined in Equations 4.10 to 4.13.

Myopic Decision Strategy

The myopic strategy only considers the utility of immediate actions at time step t to select one action for execution, as per Figure 4.9. In Equation 4.10, the action a_t^x is chosen as it has the maximum utility $u(execu, pref, a_k^x)$ for all first actions of sequences A^v to A^w at time step t available to the agent.

$$\begin{aligned} C_m(x,t) : u(execu, pref, a_t^x) = max\big(u(execu, pref, a_t^y); y = v, v+1, \ldots, w\big) \\ \rightarrow a_t^x \end{aligned} \tag{4.10}$$



(a) (b)

Figure 4.9: Actions that are not covered are considered in a *myopic decision strategy* with calculations at (a) $t = 0$ and (b) $t = 1$.

Sophisticated Decision Strategy

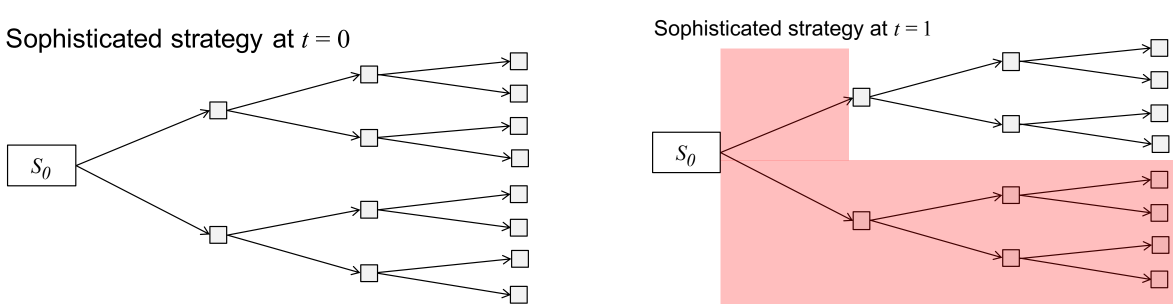
Here, the sequence chosen is one that minimizes the difference between the utility of immediate actions and the maximum possible sequence utility starting at the current time step t, as per Figure 4.10. In Equation 4.11, action a_t^x is chosen as it has the lowest difference between its utility and that of the highest-ranked sequence between A^v and A^w that follows it.

$$
\begin{aligned}
C_s(x,t) : \Big(1 - abs\big(u(execu, pref, a_t^x) - maxU(x)\big)\Big) = \\
max\Bigg(1 - \Big(\big(u(execu, pref, a_t^y) - maxU(y)\big)\Big); y = v, v+1, \ldots, w\Bigg) \\
\rightarrow a_t^x
\end{aligned}
\tag{4.11}
$$

To identify the sequence x at time step t with the maximum utility $U(A^x)$, $maxU(x)$ is defined as:

$$maxU(x) = max(U(A^x) : x = i, i+1, \ldots, j) \tag{4.12}$$

where the agent can choose between sequences i to j at time step t, and $U(A^x)$ is defined in Section 4.4.3.



(a) (b)

Figure 4.10: Actions that are not covered are considered in a *sophisticated decision strategy* with calculations at (a) $t = 0$ and (b) $t = 1$.

Resolute Decision Strategy

Finally, the resolute strategy selects the sequence with the highest sequence utility at time step $t = 0$, and commits to that sequence until reaching the end at some time step $t > 0$, as per Figure 4.11. For the initial state S_0, there exists an action a_k^x in sequence A^x where $U(A^x)$ is the highest maximum utility of sequences A^v to A^w, as per Equation 4.13. Action a_t^x is then chosen for execution.

$$C_r(x,t) : \Big(U(A^x) = max\Big(U(A^y); y = v, v+1, \ldots, w\Big) \\ \rightarrow a_t^x \qquad (4.13)$$

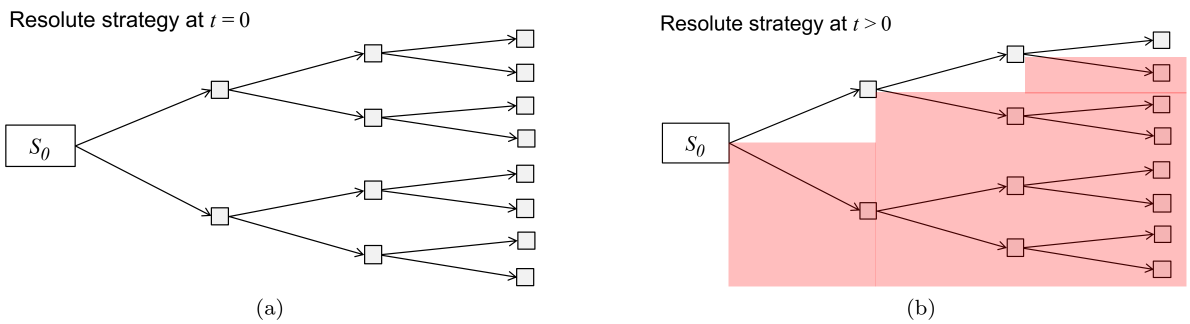


Figure 4.11: Actions that are not covered are considered in a *resolute decision strategy* with calculations at (a) $t = 0$ and (b) $t > 0$.

Emotional Impact on Decision Strategy

Whether an agent relies on $exp(t)$ or $ecoc(x)$ is again especially important when dealing with bounded agents. While it is not always possible to predict how an agent's preferences will change, relying on the neoclassical $exp(t)$ function assumes the agent is starting at a low expectancy of success that continually increases over time. A utility that always increases cannot be assumed for all agents, and behaviour that cycles through optimistic and pessimistic stages is more realistic. ECOC provides the ability to assign high utility at first, focusing on important goals, then increasing over time in the second half of the sequence. Agents relying on the myopic or sophisticated strategy have the chance to readjust their choices if expected utility is too low at future time steps.

If a goal becomes less important later on, it can be easily abandoned through a recalculation of its utility. The resolute strategy does not have this ability to recalculate. Hence, any anticipated change in goals and action utility must be predicted at time step $t = 0$. For agents with a low $BR\text{-}E(C)$ bound, goals later in longer sequences will not be evaluated or satisfied. The ECOC utility function ensures that a portion of important goals are completed first, before a continuously increasing function is applied during the "hopeful realism," "informed optimism," and "success" stages.

4.4.5 Bounded Decision Strategies

Like the observer during the tree construction phase, the agent is bounded during the execution phase. The type of strategy the agent employs determines how each bound limits its decisions.

Information Bound

Since the observer is evaluating the agent, it needs a more complete view of the world than the agent. It is assumed, then, that the agent has a lower information bound than the observer, so that $AS\text{-}BR \subseteq AS\text{-}C$, $S\text{-}BR \subseteq S\text{-}C$, and $G\text{-}BR \subseteq G\text{-}C$. It follows then that the observer *assumes* it can construct a decision tree that captures all sequences an agent can think of and use during the execution phase. It is up to the agent to select a sequence to follow using its decision strategy and goal ranking.

Cognitive Bound

In addition to knowing a subset of the observer's knowledge, the agent is also more limited in the depth used to evaluate sequences. During the tree construction phase, the cognitive bound $BR\text{-}C(C)$ limits the depth of the decision tree being constructed. During the execution phase, $BR\text{-}E(C)$ limits how deep into the decision tree an agent looks to calculate sequence utility, where $BR\text{-}E(C) < BR\text{-}C(C)$. The resolute and sophisticated condition functions $C_r(x,t)$ and $C_s(x,t)$ calculate sequence utility up to a sequence length of $BR\text{-}E(C)$. Since the condition function for each strategy is different, there is no guarantee that the same bound and starting time step will result in the same sequence being selected. The myopic strategy is not impacted by the cognitive bound of the agent $BR\text{-}E(C)$ since the myopic condition function $C_m(x,t)$ only considers its immediate actions without looking ahead in the path.

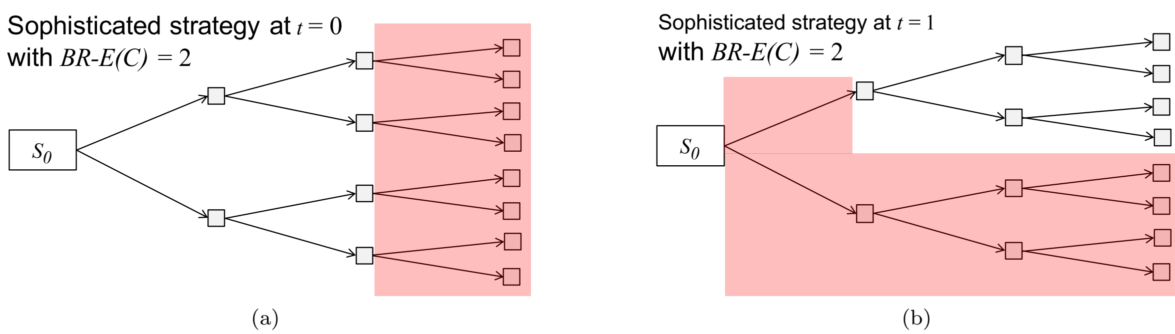


Figure 4.12: Actions that are not covered are considered for bounded *sophisticated decision strategy* calculations with $BR\text{-}E(C) = 2$ at (a) $t = 0$ and (b) $t = 1$.

Bounded Sophisticated Decision Strategy: The sophisticated strategy calculates all utilities from the current time step t, based on the current state of the world S_t. The cognitive bound limits the agent to only consider a sequences of length less than or equal to $BR\text{-}C(C)$, as per Figure 4.12 (a). At the next time step, the agent can recalculate its utility starting at $t+1$, as per Figure 4.12 (b). At each time step, the agent looks ahead further into the tree and sees a more complete view of available sequences.

Bounded Resolute Decision Strategy: As with the sophisticated strategy, the resolute agent is also limited by evaluating only sequences of length less than or equal to $BR\text{-}C(C)$. In contrast to the sophisticated strategy, however, the agent cannot reevaluate its situation at time step $t+1$, as per Figure 4.13. The bounded resolute strategy commits the agent to executing the originally chosen sequence up to length $BR\text{-}E(C)$ without reevaluation. As a result, it is possible the agent could be limited to a "partial" sequence, satisfying only a subset of the goals. In such cases it is especially important that preferred goals are satisfied first in the sequence. Section 4.4.7 discusses the role Maslow's hierarchy

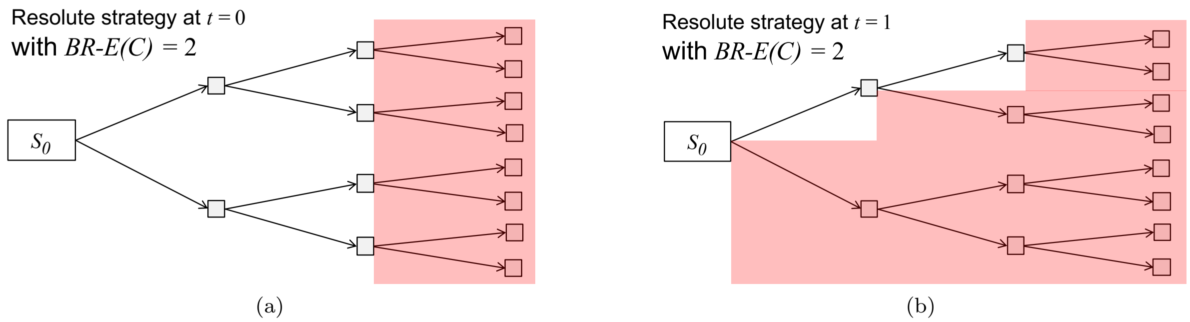


Figure 4.13: Actions that are not covered are considered for bounded *resolute decision strategy* calculations with $BR\text{-}E(C) = 2$ at (a) $t = 0$ and (b) $t = 1$.

plays to ensure this.

4.4.6 Time Bound

Like the observer's time bound $BR\text{-}C(T)$ during the construction phase, the time bound $BR\text{-}E(T)$ limits the number of states in the search space an agent evaluates during the execution phase. For the myopic strategy, if $BR\text{-}E(T)$ is greater than the number of actions to choose from at each time step, the agent is not impacted by the time bound. For sophisticated and resolute strategies, the time bound limits how much of the search space an agent can use to calculate sequence utility and pick the sequence that maximizes it. As Figure 4.14 illustrates, due to the time limit, agents will not see entire sequences in the latter part of the decision tree. They are limited to those sequences that were presented first, which in turn is based on $rank(pref, s_i)$ at time step $t = 0$, the order of goal permutations chosen to construct the tree.

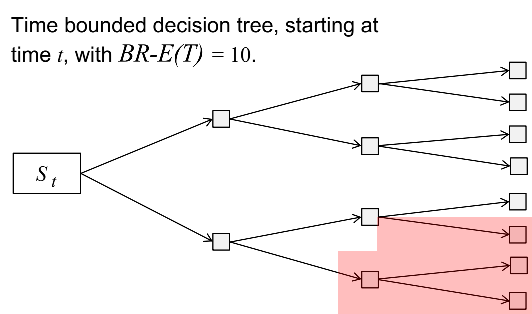


Figure 4.14: Actions that are not covered are considered for bounded *sophisticated* and *resolute decision strategy* calculations with $BR\text{-}E(T) = 10$ at t.

Note that BRAMA uses depth-first search over breadth-first or best-first search [136]. Breadth-first search is not used so as to ensure that at least one sequence is found before the time bound is reached. Best-first search is not used since an action's utility, and the "best" branch to search on, is not known until the entire sequence is found. Recall from Section 4.4.3 that the utility for some action a_k^x in sequence A^x relies on the weight aw_k^x in Equation 4.5. This weight considers the relative position of the action in the subsequence $A^x(s_i)$ towards an MH goal proposition in $s_i \in G\text{-}BR^U$. The position of this future goal in the sequence must be known before calculating what the "best" action is at the k-th position in sequence A^x.

4.4.7 Importance of Maslow's Hierarchy in Bounded Agents

Incorporating $u(pref, s_i)$ in the utility calculation is especially important for cognitively bound agents relying on the resolute strategy. The utility highlights not just which goal order has the highest utility, but also which sequence satisfies most important goals first, according to MH order. Recall from the discussion about a bounded resolute decision strategy in Section 4.4.5 that, since $BR\text{-}E(C) < BR\text{-}C(C)$, it is possible that an agent relying on resolute strategy will only consider a "partial" list of actions in a sequence. For myopic and sophisticated strategies the agent has an opportunity to consider actions past $BR\text{-}E(C)$ by recalculating utility at the next time step. The resolute strategy, however, does not allow the agent to see past this limit. This "partial" sequence available to the agent between $t = 0$ and $t = BR\text{-}E(C)$ may not satisfy all of the agent's goals. With the use of $u(pref, s_i)$, sequences that satisfy lower MH-level goals sooner result in a higher utility.

4.5 Discussion

Unlike single decision theory, sequential decision theories such as dynamic choice theory allow an observer to evaluate an agent's changing preferences over time. Due to bounded rationality, the factors that dictate which action an agent chooses are often hidden from the observer, and often from the agent as well. The observer is aware of the possible actions an agent can make, based on the goals it satisfies and required preconditions. This information is used to construct possible sequences of choices an agent can make. The sequences are limited to the observer's perception of the agent's goals and constraints imposed on available actions. While many preference indicators are hidden from the observer, axiom BR-3 shows how the observed practical order of goals and actions contribute to the sequence utility calculation. This axiom, however, breaks Savage's fourth axiom in Section 2.3.4 that requires the outcome to be independent of sequence utility. From the observer's perspective, such independence would hide the agent's preferences under a complex network of contributing factors. If the preconditions and postconditions of actions are known, an observer could infer why an action was executed before another, and why this may be contrary to the agent's presumed goal ranking.

Hence, the agent's preferred goal ranking can be based on a combination of functional order and basic MH needs. Functional order can be imposed by action preconditions and the postconditions each action contributes towards satisfying goals. Maslow's hierarchy can assist the observer in categorizing the possible basic needs an agent has. Although MH provides a ranking based on the hierarchy, it is unrealistic to assume the MH order is the one preferred by the agent. Goal semantics provide a framework for mapping agent goals to basic MH needs, conditional mappings that may change over time, and functional mappings that impose a causal order.

During the execution phase, the observer can attempt to infer goal order based on the choices an agent makes over time following one of the constructed sequences. During this phase, the MH order is used to evaluate the utility of goals and actions in a sequence, regardless of the initial goal order when the sequence was constructed. An agent can then change its preferred order by recalculating sequence utility and choosing the order that maximizes that utility. The initial goal order assumed to be the agent's preferred order $rank(A, s_i)$, selected sequence A^x, and practical goal order $rank(x, s_i)$ for outcome O^x all play a part in revealing the agent's true preferred goals.

The agent can rely on one of the three decision strategies defined by DCT, providing the observer with a way to interpret the agent's reasoning process. The myopic strategy is highly responsive to unforeseen changes but shortsighted. It only considers utility of immediate actions that are recalculated at each time step. The sophisticated strategy has two key drawbacks. First, when making a decision the agent does not consider what actions were taken beforehand. The only connection to the past is the goals that have been satisfied ($G\text{-}BR^S$). Second, the agent cannot compare the newly expanded sequence to previously considered sequences that were not chosen. In contrast to these two responsive strategies, the benefit of the resolute strategy is that the agent is not impacted by future changes in goal preferences, since utility is not recalculated once the agent commits to the first path selected. The drawback, however, is that any goals that fall after the cognitive limit in the sequence are not satisfied. The agent commits to its original sequence without reevaluating its options and utility.

Finally, rather than simply relying on the number of goals achieved, sequential DT enables expected utility calculation to reveal where in the goal achievement process an agent is. Neoclassical expected utility assumes improvement at each time step. An emotional agent, however, goes through multiple cycles, and the time dimension reveals whether the agent is in a pessimistic or optimistic stage. Each type of stage dictates whether an agent will respond negatively or positively to an action based on a point in time. A response that can change from positive to negative is in stark contrast to other architectures where an agent's emotional response to a particular event is statically assigned *a priori*, as discussed in Section 2.4.4.

4.6 Conclusion

Sequential decision theories like dynamic choice theory provide a model of behaviour that captures possible utility calculations an agent relies on to make decisions in a rational manner over time. Reasoning and ranking of preferences is a difficult process in a dynamic environment. An observer has several factors to choose from for interpreting an agent's reasoning process and changing goal preferences. The observer is bounded, so can only attempt to infer agent preferences with limited knowledge about what the agent might do. The time dimension provides an observer with the ability to evaluate patterns of behaviour over time rather than just through individual choices. Bounded rationality also restricts what knowledge the agent can use to make decisions, whether that represents actions to use, goals to pursue, or complexity of the reasoning process. Maslow's hierarchy allows for ordering and grouping of preferences to organize goals in ways that an agent may pursue, revealing more knowledge hidden from the observer. Finally, an agent's emotions impact its ability to make decisions, with ECOC providing a pattern that captures how those emotions may change over time.

The extended BRAMA still lacks an explanation for what triggers an agent's preferences to change. For myopic versus resolute agents, we can infer that individual preferences are ranked differently than an entire sequence, but there is no guarantee that an agent will exclusively use one strategy over another. In fact, past studies have shown rational agents are not consistent with their preferences and do not always rely on a single decision strategy [112]. Agents are much more dynamic due to various factors hidden from the observer which introduce noise into the preference inference process. In short, a framework based on subjective decision theory and dynamic choice theory is inadequate for emulating an autonomous agent interacting with a dynamic environment. The practical goal order for the chosen sequence gives the observer an indication as to which decision strategy results in the final goals pursued in the final outcome, as per axiom BR-3. An outstanding research question is how preferences actually change, why, and how decision strategies can be represented through the agent's cognitive abilities, rather than being hardwired as a particular decision strategy and utility calculation. In the next chapter, BRAMA is extended to include methods that consider possible combinations of sequences and highlight which preferences change due to cognitive, time, and emotional bounds of the agent. In addition to Savage's independence axiom, decision theory axioms are evaluated to identify those that are preserved in the new extension to BRAMA and which are not.

Chapter 5

Human-Centric AI Planning

5.1 Introduction

This chapter extends the BRAMA framework using AI planning to produce a high-fidelity representation of a rational but bounded agent interacting with a dynamic environment. The proposed extension allows for the representation of utility calculation as well as action sequence generation, selection, execution, monitoring, and replanning from the perspective of a human-like agent. The final result is a high-fidelity agent model capable of emulating rational behaviour that may seem irrational to an observer. For BRAMA to emulate an agent's behaviour, it must select a sequence from those generated by the agent, within the agent's bounds and preferred goal ranking. The agent must then select a dynamic decision strategy that frees it from choosing one strategy over all others. Rather than recalculate sequence utility at every step (myopic or sophisticated) or not at all (resolute), the new BRAMA agent monitors plan execution and dynamically recalculates utility at different time steps. The trigger for recalculating utility is controlled by the agent's emotional state. A new threshold is introduced that represents the minimum utility value before an agent recalculates sequence utility and reranks its goals.

According to axioms defined by subjective and sequential decision theories, not all agents are sufficiently adaptable to adjust to such dynamic environmental changes. Either they have required beliefs and can follow strategies that lead to satisfying goals in a rational way or they do not. For a BRAMA agent to emulate the level of adaptability exhibited by human-like agents, certain decision theory axioms can be preserved, some cannot, while others can be extended. This type of evaluation of decision theories should be guided by human-like characteristics like Maslow's hierarchy of needs and the emotional cycle of change.

In Section 5.2, BRAMA framework terms are reintroduced and redefined to extend the framework with AI planning for bounded human-like agents. In Section 5.3 the limitations of decision theories introduced in Chapters 3 and 4 are evaluated in the context of human-like AI planning. Axioms BR-4 to BR-9 are provided to explicitly define new relations between plans required for bounded AI planning. Section 5.4 introduces the BRAMA AI planning algorithm, STRIPS-BR, which generates plans for bounded agents. Section 5.5 introduces and contrasts different goal rankings and how they are used in BRAMA. Section 5.6 discusses the role of executing plans and how it impacts a bounded agent interacting with a dynamic environment. In Section 5.7 a simulation environment is introduced in which a BRAMA agent executes and revises its plans and reranks its goals. This chapter finishes with a discussion and concluding remarks in Sections 5.8 and 5.9.

5.2 Extending BRAMA using AI Planning

This section introduces terms used to extend BRAMA to emulate agent decision making by means of AI planning. BRAMA retains the terms defined in Chapter 3 in Table 3.2 and Chapter 4 in Table 4.1. Terms in Tables 4.3 and 4.4 are merged as agent bounds used during plan generation and execution phases, as per Table 5.1. Since agent bounds are used in both the plan generation and execution phases, $BR\text{-}C(x)$ and $BR\text{-}E(x)$ are combined into a single bound $BR\text{-}A(x)$, identified with 'A' indicating agent bounds. Terms for calculating sequence utility in Table 4.2 are adopted and redefined to calculate plan utility, as per Table 5.2.

Table 5.1: BRAMA agent bound terms for AI planning

Term	**Description**
S_t	State of the world, meaning what propositions are true at time t.
$S\text{-}BR$	State of the world the agent knows about within its knowledge bound.
$t(s_i)$	A proposition s_i that, when $t(s_t) \in S\text{-}BR$, is explicitly known to be true.
$not(s_i)$	A proposition s_i that, when $not(s_t) \in S\text{-}BR$, is explicitly known to be false.
$G\text{-}BR$	Goal propositions an agent wants to be true, mapped to an MH level.
$G\text{-}BR^I$	Interim goal propositions an agent wants to be true that are not mapped to an MH level but identified during the plan generation phase.
$G\text{-}BR_t^U$	A set of unsatisfied goal propositions at time step t, where $G\text{-}BR_t^U \subseteq G\text{-}BR \cup G\text{-}BR^I$ and $\emptyset = G\text{-}BR_t^U \cap S\text{-}BR_t$.
$G\text{-}BR_t^S$	A set of satisfied goal propositions at time step t, where $G\text{-}BR_t^S \subseteq G\text{-}BR \cup G\text{-}BR^I$ and $G\text{-}BR_t^S \subseteq S\text{-}BR_t$.
$G\text{-}BR_t^{U+S}$	A set of all goal propositions for an agent at time step t, where $G\text{-}BR_t^{U+S} = G\text{-}BR_t^U \cup G\text{-}BR_t^S$, and $G\text{-}BR \subset G\text{-}BR_t^{U+S}$.
$AS\text{-}BR$	Actions the agent knows about within its finite memory, used during the plan generation phase, where $AS\text{-}BR \subseteq AS\text{-}cor \cup AS\text{-}inc$.
$BR\text{-}A(I)$	The agent's limited knowledge about the state of the world used during plan generation and execution phases, where $BR\text{-}A(I) = \{S\text{-}BR, G\text{-}BR, AS\text{-}BR\}$.
$BR\text{-}A(C)$	Cognitive bound during the plan generation and execution phases that limits an agent's search tree depth.
$BR\text{-}A(T)$	Time bound during the plan generation and execution phases that limits the number of states in the search space used to construct and evaluate the search tree.

Terms in Table 5.1 define agent bounds during the plan generation and execution phases. The state of the world S_t is what is true at time step t. The state of the world the agent believes to be true is $S\text{-}BR$. A proposition s_i that is true or believed to be true is a member of S_t and $S\text{-}BR$, respectively. The proposition is assumed to be false otherwise, as per the closed-world assumption [261]. However, we may also want an agent to know explicitly that something is false. For example, the goal to not be hungry is a negation of the proposition "being hungry". To explicitly state that an agent has a goal of not being hungry we must be able to explicitly state this as a proposition in $G\text{-}BR$. The formalism defined in Chapter 4 only allows for the implicit definition of such goals by excluding them from $G\text{-}BR$. To explicitly state that a proposition is known to be true or false, BRAMA introduces the proposition

Table 5.2: BRAMA plan generation and execution terms for AI planning

Term	**Description**
MH	A mapping between an agent's goal propositions and Maslow's hierarchy, based on data or provided *a priori*.
$rank(pref, s_i)$	Ranking of goal $s_i \in G\text{-}BR$, where $pref \in \{MH, A, x\}$ for MH-level ranking based on MH mapping, agent's preferred ranking, and practical ranking produced by plan P^x in outcome O^x.
P^x	Plan P^x is a sequence of actions generated by the STRIPS-BR planner for the agent and uniquely indexed by x, given an initial goal order $rank(pref, s_i)$, resulting in outcome O^x with goal order that is ranked by $rank(x, s_i)$.
$P^x_{i,j}$	Partial plan $P^x_{i,j}$ represents a portion of plan P^x between time steps $t = i$ and $t = j$, inclusively.
$U(execu, pref, P^x_{0,t})$	Expected utility for plan P^x at time step t.
$exp(t)$	Neoclassical expected utility function at time step t used during the plan generation and conditionally during the plan execution phases for agents. The progress of agent relying on $exp(t)$ is always increasing.
$ecoc(x)$	Expected utility based on ECOC function used conditionally during the execution phase.
$demo()$	Agent demographics or characteristics.
$planu$	Search utility used during the plan generation phase, where $planu \in \{none, noneswap, planutil, planutilswap\}$.
$execu$	Utility function used during the execution phase, where $execu \in \{exp, ecoc\}$.
$strategy$	Decision strategy used by the agent, where $strategy \in \{myopic, sophisticated, resolute\}$.
$ecoc\text{-}th$	ECOC threshold, where $ecoc\text{-}th \in [0, 1]$.
$action\text{-}th$	Action threshold, where $action\text{-}th \in [0, 1]$.
$\mathbb{M}$	Agent simulation model, where $\mathbb{M} = \{demo()$, $BR\text{-}A(I)$, $BR\text{-}A(C)$, $BR\text{-}A(T)$, $execu$, $G\text{-}BR^U_0$, $strategy$ $pref$, $planu$, $ecoc\text{-}th$, $action\text{-}th\}$, as per Equation 5.3.

modifiers $t(s_i)$ and $not(s_i)$. When $t(s_i)$ is a member of S_t or $S\text{-}BR$ it is known or believed to be true. When $not(s_i)$ is a member of S_t or $S\text{-}BR$ it is known or believed to be false. If $not(hungry) \in G\text{-}BR$, the agent has a goal of not being hungry. During the goal generation phase the agent can now pursue some action a_m where $not(hungry) \in ADD_m$.

During plan generation and execution phases, goals are satisfied and interim goals are added from one time step to another. The interim goals an agent identifies during the plan generation phase are $G\text{-}BR^I$. $G\text{-}BR^U_t$ and $G\text{-}BR^S_t$ are the unsatisfied and satisfied goal propositions at time step t. All goals at time step t are then the union of unsatisfied and satisfied goal propositions $G\text{-}BR^{U+S}_t$. $AS\text{-}BR$ is the bounded action schema used by the agent to generate plans and calculated plan utility that may include actions from both $AS\text{-}cor$ and $AS\text{-}inc$. $BR\text{-}A(I)$ represents the agent's knowledge that stores its perceived state of the world, their goals, and action schema. $BR\text{-}A(C)$ is the cognitive bound limiting the depth of the search tree during the plan generation phase and depth of plan utility calculation during the plan generation and execution phases. $BR\text{-}A(T)$ is the time bound limiting the number of states used to construct and traverse the search tree during the plan generation phase.

Table 5.2 lists new, redefined, or extensively referenced terms used for plan generation and execution phases. MH is the mapping between an agent's goals and its MH levels. The function $rank(pref, s_i)$

with $s_i \in G\text{-}BR_t$ provides the rank of goals at time step t. When $pref = A$, the agent's preferred goal ranking is used and the goal order relation is defined by $\succ_A$. When $pref = MH$, goal ranking is based on Maslow's original order, an MH mapping, and the goal relation $\succ_{MH}$. P^x is a redefinition of action sequences A^x from Chapter 4, as plans, where plan is a sequence of actions generated with a goal-driven planner (see Section 5.3.2 for an indepth discussion). A partial plan $P^x_{i,j}$ is a subsequence of actions in P^x between times $t = i$ and $t = j$, inclusively, that were executed. $U(execu, pref, P^x_{0,k})$ is the plan utility from the beginning to the k-th action. It redefines the original sequence utility $U(execu, pref, A^x)$ for plans:

$$U(execu, pref, P^x_{0,k}) = \frac{\sum_{i=0}^{k} U(execu, pref, a^x_i)}{|P^x|} \tag{5.1}$$

Functions $u(exp, pref, a^x_t)$ and $u(ecoc, pref, a^x_t)$ are utilities assigned to action a^x_k relative to its add-propositions and lowest unsatisfied MH-level goal proposition, as defined in Equations 4.2 and 4.3. For interim actions that satisfy interim goals, $u(execu, pref, a^x_t)$ is a utility assigned to action a^x_k if it satisfies an interim goal, as defined in Equation 5.2 in Section 5.5. Functions $exp(t)$ and $ecoc(x)$ are the expected utility functions defined in Chapter 4.

During the plan generation phase, the agent relies on $exp(t)$ to calculate its utility. It assumes it is well equipped to predict expected utility in a rational manner. During the execution phase, the agent relies on either the neoclassical or ECOC-based utility function, where $execu \in \{exp, ecoc\}$. If $execu = exp$, the agent was realistic about its abilities during the plan generation phase. If, however, $execu = ecoc$ then the agent was not realistic, has an emotional response to the real consequences of its actions during the plan execution phase, and ultimately may require replanning.

During execution the agent monitors its plan by recalculating plan utility at every time step t. To control when replanning is required, two thresholds represent an agent's ability to execute a complete plan. These are briefly introduced here and discussed further in Section 5.7. The first threshold is *ecoc-th*, which acts as a lower bound on the minimum plan utility an agent can handle before pausing execution. If $U(execu, pref, P^x_t)$ falls below this threshold the agent stops execution and begins to identify goals that should be deferred until a later time. Goals are not evaluated directly through the utility of a goal proposition. If this was the case, then goals at lower *pref* rankings would simply be selected for deferment. Instead, action utility is used to decide which goals to defer by identifying goals satisfied by actions that are least probable to succeed. The second threshold provided by BRAMA is *action-th*. Any action with an expected utility $U(execu, pref, a^x_t)$ below this threshold for plan P^x at time step t is selected. Any goals that are satisfied by the selected actions are deferred. With the remaining goals, replanning occurs where a new search tree is constructed, from which a plan is selected and executed. The new plan, say P^y, is combined with the executed portion of the previous plan, say $P^x_{i,j}$, that was executed from times $t = i$ to $t = j$, forming a new plan $P^{x \cup y}$, where $P^x_{i,j} \cup P^y = P^{x \cup y}$.

Finally, BRAMA incorporates a simulation to test "what-if" scenarios for different agent models $\mathbb{M}$. In Section 5.7, the simulation is introduced. Tables 5.3, 5.4, and 5.5 define terms used to configure the simulation agent model and environment.

5.3 Subjective and Sequential Decision Theory as a Planning Problem

While subjective and sequential decision theories allow an observer to calculate utility of goals and plans from observed behaviour, some subjectivity is based on bias and emotional mood that may not be observable. For example, many models in economics have attempted to incorporate bounded rationality with varying degrees of success [208]. This section evaluates such limitations in the context of AI planning for human-like decision making.

In order to extend BRAMA to incorporate an AI planning algorithm from the agent's perspective, several elements of subjective and sequential decision theories must be abandoned as they no longer apply. The analysis for basing a planning problem on decision theory has been done by Haddawy and Rendell [102]. They concluded that while AI planning focuses on plan generation and representation, decision theory limits itself to only representing beliefs and desires. A knowledge gap exists within decision theory about belief revision and causality. Combining belief revision with either a causal a or goal-driven plan sequence generation would create powerful representation languages for the emulation of goal-driven agents.

A successful representation of a planning problem in STRIPS first introduced in Section 2.4.2 and based on decision theory has also been demonstrated by Feldman and Sproull [80]. They outlined how a combined model can address issues like uncertainty, replanning, and weighing the costs of a changing strategy. This section continues such comparative analysis by evaluating axioms introduced in Section 2.4, outlining which are preserved in bounded human-centric AI planning and which are not. Some are extended to accurately incorporate human-centric bounds into a planning reasoner. The preserved and extended axioms lay the foundation for a planning algorithm introduced in Section 5.7.1. This algorithm allows an agent to dynamically respond to changes in the environment by triggering utility recalculation and replanning processes.

5.3.1 Decision Theory is Insufficient for Human-Centric AI Planning

A human-like rational agent is deliberate in the generation and selection of plans to execute. It evaluates multiple possible worlds, actions, and outcomes that satisfy its goals and chooses a course of action that maximizes its utility. Sequential decision theory takes a more passive, opportunity-driven approach to plan generation and consideration of different sequences [102]. While the sequence selection process of decision theory is rational, the sequence generation process is not. Instead, decision theory, whether single, sequential, or subjective, is *opportunity* driven [102]. The generation of sequences is not guided by goals. Sequences are generated that transition states into some new states that may or may not satisfy goals. The sequence of actions that maximizes utility is then selected as the "best" plan. The algorithm for generating the sequence is independent of the goals themselves.

For an agent to act rationally and be goal driven, the search tree construction process must be goal driven and rational as well. To emulate such a rational agent, an goal-driven search must be performed to find a sequence that matches an agent's behaviour. In Chapter 4, an observer relied on a goal-driven postcondition-based heuristic to efficiently generate plans that are possible within the observer's bounded knowledge and cognitive resources. Starting with a unique order of goals, the first "reasonable" sequence that satisfied those goals was selected. The observer did not iterate through all possible combinations of actions that could satisfy a particular order of goals. Hence, in sequential DT, this heuristic was only used to find the first executable sequence, not one that maximizes utility. Many AI planning algorithms implement a goal-driven plan-generation process, as well as a rational plan-selection process. Focusing on a single agent with a specific goal order, it is possible for a reasoner to generate a variety of sequences within their bounds and select the best one. As will be discussed in the next section, axioms defined for subjective and sequential DT need to be revisited to correctly emulate human-like decision making.

5.3.2 Preservation of Decision Theory Axioms

AI planning has many similarities with subjective and sequential decision theories as well as key differences. Jeffrey's decision theory described in Section 2.3.4 introduces predicates assigned to utilities and probabilities. Different truth-value assignments make it possible to evaluate a sequence of choices when propositions are true or false in different worlds. Hence, a sequence in one world may have a different utility in another world. For example, a search tree constructed during the plan generation phase can be executed under different truth-value assignments, causing the plan execution to fail. Replanning offers opportunities for an agent to reevaluate its goal preferences, constraints, and truth-value assignments about the state of the world that were incorrectly assumed to be true or false during previous plan generation phases. According to Jeffrey, the order of goals is based on the agent's preferences by assigning probability of success to each goal. Subgoals that must occur before transitioning to a goal have lower utility. Such subgoals may also be associated with a negative utility and considered a "cost" [13].

Finally, as Haddawy points out, the algorithm for generating sequences is opportunity driven, and independent of the goals [102]. A plan, then, is simply a sequence of choices that was created by some goal-driven algorithm. A rational plan is a sequence of actions that maximizes utility of the sequence of choices. Probability is based on beliefs of the agent either as Bayesian probabilities or some type of expected-value function. As discussed in Section 2.3.4, information about probabilities is not always available. In those cases, an expected-value function is used to infer such probabilities. As Feldman points out, for planning problems these are the types of monotonically increasing functions discussed previously [80], and defined in BRAMA by the neoclassical utility function $exp(t)$. In fact, non-monotonic functions are used only when explicitly defined *a priori* by an individual for a set of independent choices or if calculated from data.

The decision theories discussed in this thesis have several axioms and assumptions that must be true to be used for emulating human-like utility calculations. However, only a portion of these axioms are preserved in human-centric and bounded AI planning, namely those that evaluate entire sequences rather than individual decisions. A key reason for this is the role Maslow's hierarchy plays in the calculation of utility. Each goal's utility calculation is relative to the MH level of other goals satisfied in the plan, while emotions change depending on how far along an agent is in its plan. Single DT does not capture this relation among goals and is not suitable for human-like utility. Sequential DT better captures this relation, but, as will be discussed, has its own limitations. Finally, some axioms that are not preserved are instead replaced with axioms more suitable for use in AI planning and BRAMA to calculate human-like utility.

Subjective Decision Theory Axioms Not Preserved in AI Planning

The *transitivity* axiom VNM-2 is a useful requirement when inferring agent preferences from observed behaviour. This is especially true if the behaviour occurred across multiple plans. However, transitivity is a problematic requirement and generally assumed to be a weak relation between goals rather than a strong relation [105]. As mentioned in Section 2.6.1, this is especially true for preferences and desires of human subjects in situations that are not context specific [223, 9] or are provided *a priori* [141]. Consider an agent whose goal preferences are $x \succ y$, $y \succ z$, and $z \succ x$. Any sequence with all three goals must break one of the preferences, by choosing either:

$$x \succ y \wedge y \succ z \implies z \nsucc x$$
$$\text{or}$$
$$x \succ y \wedge z \succ x \implies y \nsucc z.$$

The question may be which preferences are weak (can be broken) and which are strong (cannot be broken). Inferring preferences from various degrees of weak and strong preferences is referred to as revealed preferences theory [215, 224]. Preferences that are observed to be broken during execution must have weak transitivity relation. Those that are never observed to be broken may have a weak relation, but if observed often enough, indicate a significant possibility of a strong relation. Imposing environmental constraints and preconditions by creating preconditions on actions highlights strong transitivity relations by forcing an order in which certain actions must be executed. The remaining preferences can be considered as weak relations.

By observing each decision in isolation, as in single DT, it would be difficult to infer weak preferences. However, by observing the entire sequence, weak relations may become apparent. For example, knowing that x is a precondition of some action a_m with postconditions z for some action a_n in *AS-cor*, then $z \succ x$ is a strong relation. Focus can then be redirected toward the order of other states in relation to those already observed. Any variation in the order between two states highlights a weak preference relation. As observed by Simon and Feldman, preferred order between two subjective states [1] may change over time, indicating a weak preference relation [230].

During plan utility calculations in BRAMA, ordinal and cardinal utilities penalize any goals satisfied out of order, which is reflected in the sequence utilities $U(exp, pref, A^x)$ and $U(ecoc, pref, A^x)$ in Equations 4.8 and 4.9 in Section 4.4.3, jointly referred to as $U(execu, pref, A^x)$, where $execu \in \{exp, ecoc\}$. Cardinal utility is especially useful as it penalizes the degree to which goals are out of order in relation to MH. Hence, transitivity of sequence utility is maintained even if transitivity of choices is not. For goal preference MH and plans P^x, P^y, and P^z, each plan retains MH preference order. The new axiom BR-4 states that:

Axiom BR-4 (Plan Order Transitivity)

$$(P^x \preceq_{MH} P^y) \wedge (P^y \preceq_{MH} P^z) \implies P^x \preceq_{MH} P^z. \qquad \text{(BR-4)}$$

The *completeness* axiom VNM-1 is also a problematic requirement in decision theory [105]. Due to bounded rationality, it is not preserved in bounded planning. First, the knowledge bound $BR\text{-}A(I)$ and limited memory prevent an agent from having knowledge about all actions and possible outcomes, hence all states cannot be assigned a preference. Second, the cognitive $BR\text{-}A(C)$ and time $BR\text{-}A(T)$ bounds prevent a planning algorithm from constructing a search tree and visiting all states to assign a preference to them. Since Savage's axioms S-1 to S-4 assume completeness and transitivity between

[1] Simon and Feldman refer to subjective preferences as probabilistic preferences in [230].

individual choices, these are not preserved in bounded AI planning.

Changes in perception of preferences from one time step to another during execution prevent some axioms from being preserved. The *independence* axiom VNM-4 is not preserved since during execution the newly discovered outcomes of actions reduce the utility of a plan. Hence, plan utility is dependent, in part at least, on the perceived probability of outcomes for each action. Savage's axiom S-2 requires that two events are evaluated independently. However, since the independence axiom VNM-4 is not preserved, S-2 is also not preserved. Axiom S-3 (state neutrality) is not preserved since actions with highest probability of success from the current state are preferred.

Jefferey's axioms J-1 and J-2 on averaging and impartiality are not preserved due to the order imposed by preconditions and relative order imposed by MH levels. First, consider Jeffrey's *impartiality* axiom J-2. If two plans P^x and P^y finish with $U(execu, pref, P^x) = U(execu, pref, P^y)$, it is not guaranteed that a new action or goal will change their utility in the same way. If a new action a_m is added to each plan, a_m's preconditions may not be true, and changing the order of actions to accommodate the preconditions may change the utility of the plan. Say, for example, that a_m satisfies a security goal, and in plan P^x it must be the first satisfied goal while in plan P^y it must be satisfied last. According to $u(pref, s_i)$, defined in Equation 3.17, this would reduce the utility of P^y's goals that are higher than the security level, reducing $U(execu, pref, P^y)$. The new plan non-impartiality axiom states that:

Axiom BR-5 (Plan Non-Impartiality)

$$U(execu, pref, P^x) \leq U(execu, pref, P^y) \not\Leftrightarrow U(execu, pref, P^x \cup a) \leq U(execu, pref, P^y \cup a). \quad \text{(BR-5)}$$

Second, Jeffrey's *averaging* axiom J-1 is not preserved since a change in a goal's order changes its MH-level order relative to the MH level of other goals, ultimately impacting the goal's utility. Recall that J-2 states that if propositions s_i and s_j are mutually incompatible ($s_i \oplus s_j$) then choosing one over the other has no impact on the overall preferences. However, if the two propositions are postconditions of actions in plans, say P^x satisfies s_i and P^y satisfies s_j, then changing these actions in plans may not retain plan preferences. Consider such actions a^x_m and a^y_n where $s_i \in ADD^x_m$ and $s_j \in ADD^y_n$. Imagine a^x_m is able to be swapped for a^y_n in P^y and vice versa, in such a way that required preconditions are true and postconditions make necessary goals true in each new plan. The modified plans are now $P^{x'}$ and $P^{y'}$.

Even though the actions can be swapped they may undo the postconditions of other actions in modified plans they did not undo in their original plan, potentially changing the plan's utility. Even if it was possible to modify the plans in a way that did not change the order of actions, P^x and P^y may have overlapping MH levels. For example, imagine that P^x satisfies physiological and social goals while P^y satisfies security and esteem goals. It is possible that if $P^{x'}$'s social goals are satisfied first then the swapped action's security action is satisfied afterward so that the utility of $P^{x'}$ social goal will be decreased. The new goal order non-averaging axiom states that for some plans P^x and P^y with swapped actions that satisfy mutually incompatible goals, producing modified plans $P^{x'}$ and $P^{y'}$, we have:

Axiom BR-6 (Goal Order Non-Averaging)

$$P^x \leq P^y \not\Leftrightarrow P^x \leq (P^{x'} \cup P^{y'}) \leq P^y. \quad \text{(BR-6)}$$

Following the non-preservation of impartiality, Savage's and Jeffrey's *independence* axioms are not preserved since a different order of actions can produce different plan utilities. Recall that the $u(pref, s_i)$ utility defined in Equation 3.17 calculates a goal's utility based on that goal's order relative to other goals satisfied in the same plan. Hence, swapping actions between plans that impose a different goal ordering for satisfied goals may change the utility of the entire plan, as stated in axiom BR-6.

Subjective Decision Theory Axioms Preserved in AI Planning

By assuming the observer, as the policy maker or designer of AI models, is bounded we must accept that the VNM, S, and J axioms discussed in the previous section are not preserved, as they assume an omniscient observer. This limits what information can be used to emulate a subject's behaviour. This section evaluates why and how the preserved axioms impact emulation of a human-like bounded subject by a bounded observer.

There are two characteristics shared by the three preserved axioms VNM-3, S-5, and S-6 that remain. First, the utility of a sequence is used to decide between sequences, not the utility of a single action. Second, once a subject has committed to one sequence over another, a sufficiently large change in utility is required for a subject to select another sequence. In the context of AI planning, this means that the subject will select a plan with maximum utility, then execute and monitor that plan. During execution, the subject will trigger a replanning process when either: 1) a plan with a sufficiently higher utility is found or 2) the current plan's utility falls sufficiently low relative to its original utility during the planning phase.

Recall that the *continuity* axiom VNM-3 states that "no outcome is so bad that it is not worth a gamble with a sufficiently high probability of success." Hence, axiom VNM-3 is preserved because it is possible that a sufficiently large change in plan utility after replanning will prompt a subject to change their course of action and follow the new plan. Axiom S-5 (sequence indifference) states that "a subject must not be indifferent to sequences, and there must be some difference in utility between one sequence and another." Axiom S-5 is preserved because the subject is not indifferent to plan utility. If two plans have different utilities, the rational subject will prefer the plan with higher utility. If two plans have the same utility, only then is the subject indifferent to the plan. Finally, axiom S-6 (sequence non-atomicity) is preserved because a change to an already chosen plan will convince a subject to choose the new plan only if that change significantly changes each plan's utility.

Savage's axioms S-5 and S-6 describe an agent's perception of sequences, not individual choices. This allows for more flexibility in situations when a change causes a sufficiently high difference in the expectation of success. Axiom S-5 states that the agent prefers one sequence over another solely based on sequence utility. We take this as a conjecture that any rational agent that maximizes its utility can compare sequences based on its utilities using $U(exp, pref, A^s)$ and $U(ecoc, pref, A^s)$ defined in Section 4.4.3. We extend this to plans and say that, given some plans P^x, P^y and plan utilities $U(execu, pref, P^x)$ and $U(execu, pref, P^y)$ where $execu \in \{exp, ecoc\}$, the new plan non-indifference axiom states that:

Axiom BR-7 (Plan Non-Indifference)

$$U(execu, pref, P^x) \leq U(execu, pref, P^y) \iff P^x \preceq_{pref} P^y. \tag{BR-7}$$

Savage's axiom S-6, the non-atomicity axiom, is more explicit about the impact of expected utility on the sequence, and directly counters Jeffery's impartiality axiom J-1. Savage's axiom S-6 states that the plan preference $P^x \prec P^y$ is not impacted by some change r unless the probability of r is sufficiently high.

Meaning, the order of preferred plans changes only if a change has a sufficiently high impact on expected utility. A concrete condition can be given for what constitutes a "sufficient" probability. Consider plan preference relation $P^x \prec_{pref} (P^y)$, and a change r that modifies a plan P^x to $P^{x'}$. It is possible that the difference in utilities between P^x and $P^{x'}$ is large enough that the utility of $P^{x'}$ is greater than the utility of P^y by a factor greater than some threshold v. We say that, given that $P^x \prec_{pref} P^y$ and a threshold v, then for some change r that changes P^x to $P^{x'}$ it is possible that:

Axiom BR-8 (Plan Non-Atomicity)

$$\begin{aligned}&(P^x \prec_{pref} P^y) \wedge \big(U(execu, pref, P^y) < U(execu, pref, P^{x'})\big) \quad \wedge \\ &\big(v < (U(execu, pref, P^{x'}) - U(execu, pref, P^y))\big) \\ &\implies P^y \prec_{pref} (P^{x'}).\end{aligned} \tag{BR-8}$$

Consequences of Partial Axiom Preservation

The main takeaway from the analysis performed so far is that from the observer's perspective, individual choices an agent makes are insufficient to infer an agent's preferences or changes in those preferences. Relying on axioms BR-7 and BR-8, we can say that an agent's preference for one plan over another is not dependent on individual choices. Rather, the impact a change has on the entire plan must be considered. This is because a single change in the plan can modify the utility of the entire plan in a way that may or may not necessarily change plan preferences. From an observer's perspective, a change to a plan occurs during execution. Plan execution is started but only partially completed before the replanning process is triggered. At some point the plan is stopped, utility is recalculated, and replanning occurs. An executed plan for a bounded agent, then, is made up of partially executed plans. Each partially executed plan is a portion of an entire plan that was generated and selected in a rational manner, as per axiom BR-9. During execution, however, the plan was interrupted and only partially executed. The agent then continued with a new plan, also rationally constructed and selected. A rational agent is not myopic, sophisticated, or resolute. Instead, an agent is resolute up to a point when replanning is required.

Axiom BR-9 (Observable Plan)

$$P^x_{i,j} \cup P^y_{j,k} \cup \ldots \cup P^z_{v,w} = P^O. \tag{BR-9}$$

We begin with rational plans P^x, P^y, ..., P^z chosen by a rational agent during the plan generation phase. We then have partially executed plans from time steps i to w, resulting in $P^x_{i,j}$, $P^x_{j,k}$, ..., $P^z_{v,w}$. Since observable plans are only those that were executed, the observable plan P^O is the union of the partially executed plans executed by the agent from time steps i to w, as per axiom BR-9.

5.4 AI Planning with Bounded Rationality

This section presents an implementation of the three bounds in a planner called STRIPS-BR, an extension of the STRIPS planner presented in Section 2.4.2. STRIPS-BR extends BRAMA by giving the agent planning capability in addition to decision making. The agent uses the same path construction heuristics as the observer in Section 4.3.3, except that it construct a single search tree of all possible plans, given their initial preferred order $rank(A, s_i)$. The plan with the highest utility is selected for execution. During the plan generation phase, the agent uses the neoclassical expected utility $exp(t)$ and its own preferred ranking of goals $rank(A, s_i)$. During the plan execution phase the agent can use either the neoclassical utility or the ECOC-based utility function. It can also rely on one of three types of goal rankings presented in Section 5.5.

5.4.1 STRIPS-BR

The original STRIPS planner constructs a search space for a planning problem. It assumes storage space is infinite and all essential knowledge for a plan is available to the agent. This is not the case for a bounded agent, which requires the new bounded implementation STRIPS-BR. Figure 5.1 illustrates the tree construction and search algorithm for STRIPS-BR.

STRIPS-BR has new constraints required to implement the time, cognitive, and knowledge bounds, identified by dotted lines. Time and cognition bounds depend on simple conditions to check whether *state_count* for time and *depth* for cognition have surpassed their respective limits, $BR\text{-}A(T)$ and $BR\text{-}A(C)$. Bounded knowledge in $BR\text{-}A(I)$ for an agent is made up of an unknown or incorrectly presumed state of the world ($S\text{-}BR$), goal propositions the agent is aware of ($G\text{-}BR$), and a limited set of actions available to the agent ($AS\text{-}BR$). Like STRIPS and other classical planners, STRIPS-BR also makes the closed-world assumption that [261]: a statement that is true is also known to be true, and conversely, what is not currently known to be true is false. As a result, any goal states that are negative must be explicitly stated as such. For example, the goal to "not be hungry" in a closed-world system cannot be defined without an explicit label like *not hungry*. For such goals, STRIPS-BR adds proposition confirmation and negation qualifiers. For some proposition s_i, $t(s_i) \in S_t$ explicitly defines s_i as true at time step t, while $not(s_i) \in S_t$ explicitly defines s_i as false at time step t. An action's add-proposition can now explicitly specify whether an added proposition is known to be true or known to be false. Delete-propositions remove propositions from S_t, including any $t(s_i)$ and $not(s_i)$ propositions. It is now possible to define an agent that is currently hungry as $t(hungry) \in S\text{-}BR$ for "hungry," and a goal proposition of $not(hungry) \in G\text{-}BR$ for "not hungry". During the planning process, the function $get\_operator(AS\text{-}BR)$ selects and returns the next available action a_t^x in $AS\text{-}BR$.

The next step tests whether that action's add-propositions satisfy any current goals in G_t. If not, another action is selected. If it does satisfy a goal, the action's preconditions are checked to make sure they are true in S_t. If they are not, the current process pauses, and a separate search process begins to find a subplan that satisfies the preconditions first. Once complete, the subplan is appended to the current plan, resulting in a new plan P_{t+1}^x. Next, the latest action in the plan is executed, transitioning the current state of the world S_t to S_{t+1}. The cycle ends when state count, tree depth, and current time stamp are incremented. The new cycle begins by checking whether all outstanding goal propositions are already true in the current state of the world, where $G_t \subseteq S_t$. If all outstanding goals are found, the search process is complete.

5.4.2 Bounded Rationality in Planning

Knowing that human agents are bounded, how can a rational agent find the "best" plan to follow? Several factors influence the chances of finding an optimal plan to satisfy an agent's goals. This section

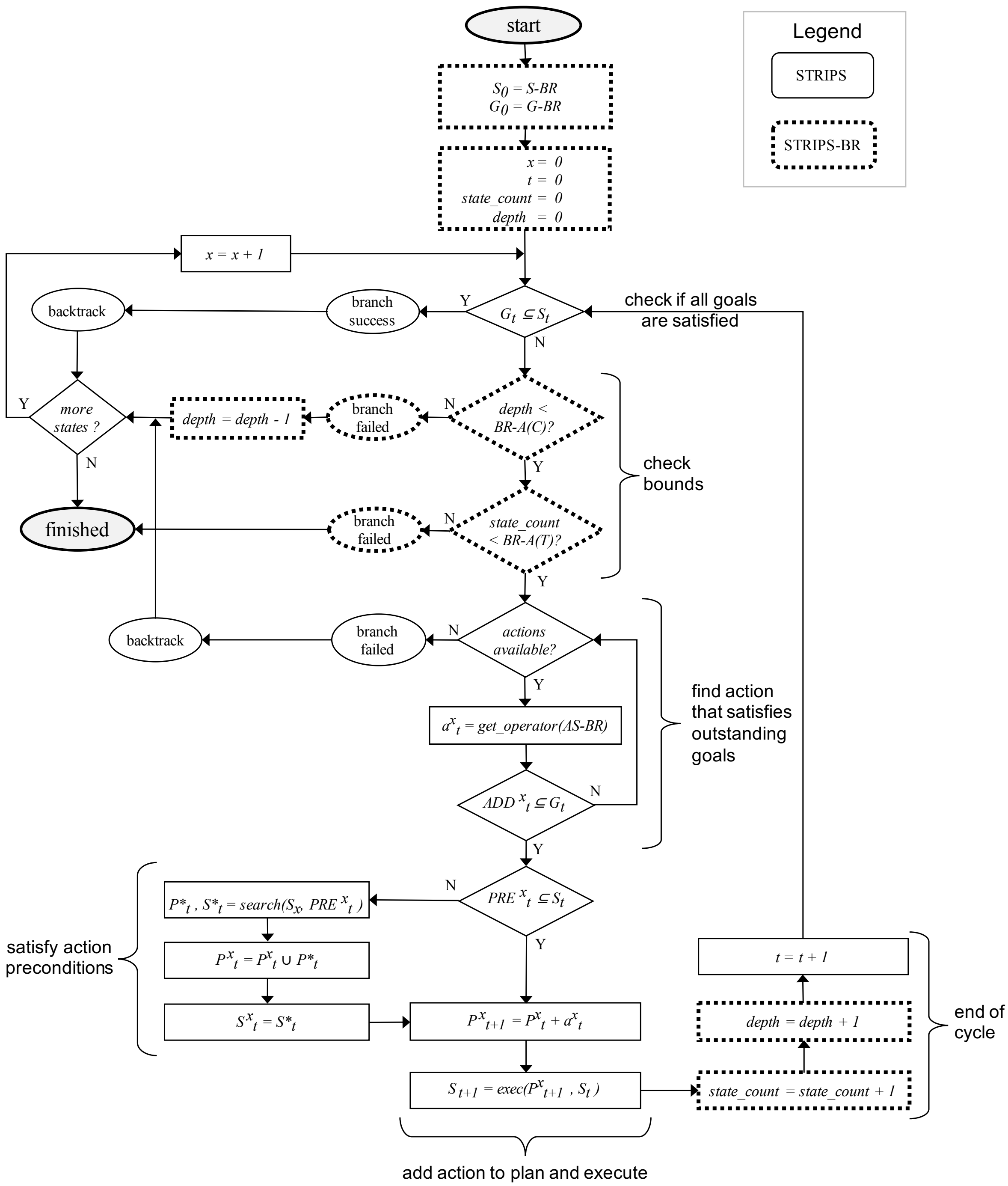


Figure 5.1: STRIPS-BR search algorithm defined in procedure $search(S, G)$ for constructing a search tree

presents methods that assist an agent to overcome its bounds. Similarly to coping strategies discussed in section 2.3.5, the human-like BRAMA agent may adapt in ways that increase the likelihood of finding any plan at the expense of finding the optimal plan.

Each bound limits the search process. The order of goals is a factor since STRIPS-BR is a means-end planner and, due to $BR\text{-}A(T)$, only the first plans found for limited variations of the initial goal order can be evaluated. Agents also need some way to order or truncate paths to ensure a greater number of shorter plans are considered rather than fewer long plans. Cognitive limitation set by $BR\text{-}A(C)$ is a practical way of truncating longer paths. $BR\text{-}A(I)$ is a factor since only information known to the agent about actions in $AS\text{-}BR$, believed state $S\text{-}BR$, and believed goals in $G\text{-}BR$ can be used to construct a search tree using the BRAMA heuristic. When combining all three bounds, we see that not all information is known by the agent, and not all combinations of actions can be included in the search tree. It is not until the execution phase that unknown environmental constraints become apparent. Hence, only during execution does the agent require flexibility to overcome differences between the generated plan and the more realistic executable plan. The impact of each bound affects the agent's performance differently when generating or executing plans.

Knowledge Bound in BRAMA

The focus of the knowledge bound for sequential DT was the observer's limitation when constructing the decision tree. Each path in the tree then served as the basis for the agent's utility calculation and decision making. In BRAMA, the agent's knowledge contains a bounded representation of the state of the world, goals, and action schema. The agent is negatively impacted if its knowledge about the world in $S\text{-}BR$ differs from the true state of the world in S_t at time step t. It is also negatively impacted if it stores incorrect actions from $AS\text{-}inc$ in its action schema $AS\text{-}BR$. Finally, mapping the correct goals to the agent's basic MH needs will determine whether satisfying those goals actually satisfies its underlying needs.

During the tree construction process, an agent applies different actions in order to satisfy its goals. The action schema $AS\text{-}BR$ contains all the actions available to the agent used to build the search tree but excludes missing actions. For example, in Figure 5.3, action a^2 is a missing action. As a result, any plan that contains action a^2 is not available to the agent, and excluded from the search tree.

A key limitation of BRAMA is that the agent does not learn new knowledge about new MH goals or available actions. The knowledge provided by $S\text{-}BR$, $G\text{-}BR$, and $AS\text{-}BR$ is static. Some actions do provide "information" propositions stored in $S\text{-}BR_t$ that can be used to satisfy preconditions of required actions. For example, knowing about a soup kitchen is a precondition to going there and getting food. The notion of knowing can be an add-proposition of another action that "informs" the agent by adding the required proposition to that agent's knowledge in $S\text{-}BR_{t+1}$.

Several options exist for overcoming the lack of knowledge. The knowledge bound is the only one of the three that can be determined directly through discussions with an individual. New knowledge can be introduced through discussions, courses, workshops, and so on. The individual's support network and social norms also play an important role in determining what knowledge may be available, preferred, or ignored by an individual. Hence the knowledge bound is largely domain specific, with different population cohorts having different types of knowledge available to them. This makes up the agent's missing, incorrect, and alternative actions and goals as defined in Section 3.3.2.

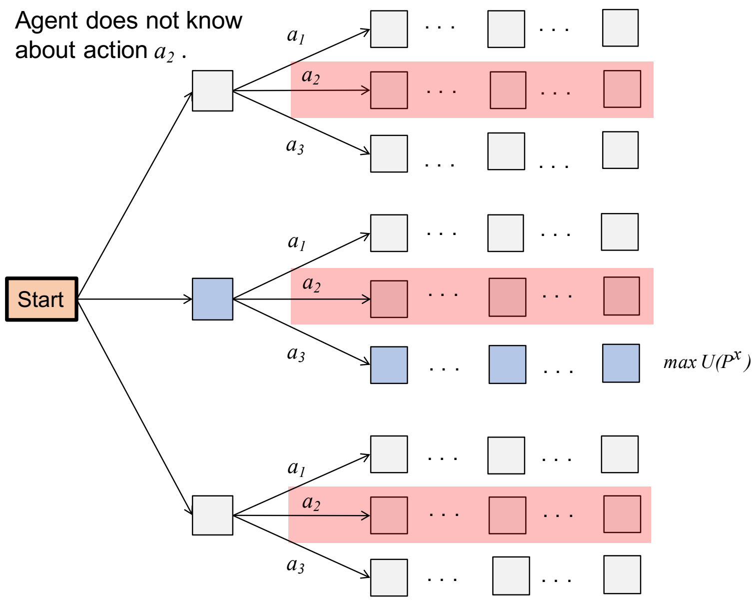


Figure 5.2: Search tree constructed with a bounded $AS\text{-}BR$, where $a^2 \notin AS\text{-}BR$

Cognition Bound in BRAMA

The $BR\text{-}A(C)$ bound limits the depth of the search tree that is traversed by the agent to find a plan, as illustrated in Figure 5.3. An obvious benefit of $BR\text{-}A(C)$ is that arbitrarily long plans are not evaluated. Assuming executable plans can be found with shorter length, this allows for more states in the search space to be visited and more plans to be found within an agent's time limit. Hence the right choice of $BR\text{-}A(C)$ can maximize the number of plans up to a certain length to be evaluated.

A drawback of a cognitive limit becomes apparent in situations where plans to satisfy goals are longer than $BR\text{-}A(C)$. For example, consider an agent with a cognitive limit of $BR\text{-}A(C) = 3$ and five goals to satisfy. Imagine the action schema only contains actions that satisfy one goal at a time. Let's call these "single-goal" actions. Using a schema with single-goal actions, an agent with $BR\text{-}A(C) = 3$ will never find a plan that satisfies five goals. If we consider that an action's preconditions also require an action to satisfy each precondition, the number of actions required grows accordingly.

A BRAMA agent must have another approach for scenarios where the number of goals and subgoals is greater than $BR\text{-}A(C)$. There are four basic solutions proposed for overcoming this problem. The first solution relies on an island-driven search [72]. By using actions that omit preconditions, a high-level abstract plan is created to reduce the exponential growth of interim goals to within the agent's cognitive limit. A new search is performed to find partial plans that transition S_t from one island-state to another. The potential use of an island-driven search is included in the discussion of future work in Section 8.4.

In the second solution, the agent's action schema must include "multi-goal" actions so that the number of actions required to satisfy goals is $\leq BR\text{-}A(C)$. For example, if at least two of the three actions are dual-goal actions and one is a single-goal action, five goals can be satisfied with three such actions.

The third solution is to employ *partial satisfaction planning* where a set of partial plans are created, where each plan satisfies a subset of goals [23]. A search tree is constructed within the cognitive limits of the agent, and a plan is selected. Any goals not satisfied by the first plan are deferred to a later time.

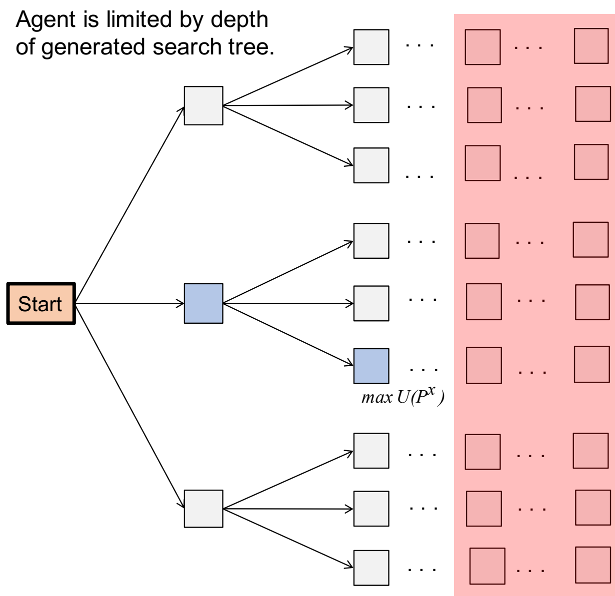


Figure 5.3: Search tree constructed with $BR\text{-}A(C) = 2$

Once goals are satisfied by the selected plan, the deferred goals are retrieved and a new search tree is constructed to satisfy the remaining goals. For our five-goal scenario, a three-action plan satisfies the first three goals, and a separate two-action plan satisfies the remaining two goals.

The fourth solution combines decision theory with AI planning and replanning techniques described in Section 2.4.4 to replicate decision strategies introduced in Chapter 4. Recall that the myopic strategy considers the utility of immediate actions only, before selecting one with the highest value. The myopic strategy can be replicated by defining an agent's cognitive limit as $BR\text{-}A(C) = 1$. This forces the agent to consider only immediately available actions by looking only one step ahead. The sophisticated strategy can be replicated with $BR\text{-}A(C) > 1$ but recalculating plan utility at each time step. Finally, the resolute strategy is similar to classic planning algorithms that do not have replanning. Having $BR\text{-}A(C) > 1$, a reasoner chooses the plan with the highest utility to satisfy the most important goals first. Once the plan is complete, a new search tree is constructed for the remaining goals. During tree construction, any path that does not satisfy all goals before reaching the $BR\text{-}A(C)$ limit remains in the tree without backtracking. Plans with the highest utility are those that satisfy goals in the agent's preferred order.

As an extension to decision theory, BRAMA incorporates this last approach, including replanning as described in Section 5.6. The BRAMA simulation environment discussed in Section 5.7.2 simulates multiple cycles of replanning by continuously generating and combining partially executed plans when replanning is triggered, hence the third solution is also required. Finally, it is possible that, given a particular domain, multi-goal actions are included in AS, as per the second solution.

Time Bound in BRAMA

The search space accessible to an agent is limited to a finite number of states. The solution to overcoming the time bound is to order goals in a practical way that align with possible plans given actions in $AS\text{-}BR$. According to bounded rationality, any computation is limited by computational time. AI planners are no exception, including STRIPS and STRIPS-BR. This bound is not just a theoretical limitation but also a practical one as planning is a computationally complex problem. The STRIPS planning problem is PSPACE-complete [37], meaning that STRIPS can find a solution to a problem with a polynomial amount of memory space using a Turing machine[2]. To ensure an agent is rational, and is maximizing its own means, STRIPS-BR must find all plans possible which are then compared against each other. The task of finding an optimal plan is also PSPACE-complete [37].

From a human-centric perspective, time depends on the situation an agent faces and how much time is practically required. In situations where an immediate response is not needed, time can be the entire time capacity of the agent. When a response is needed immediately, such as fleeing a dangerous situation during an emergency, time to find a decision is much shorter. The time bound is designed to capture both types of practical limits on computation time.

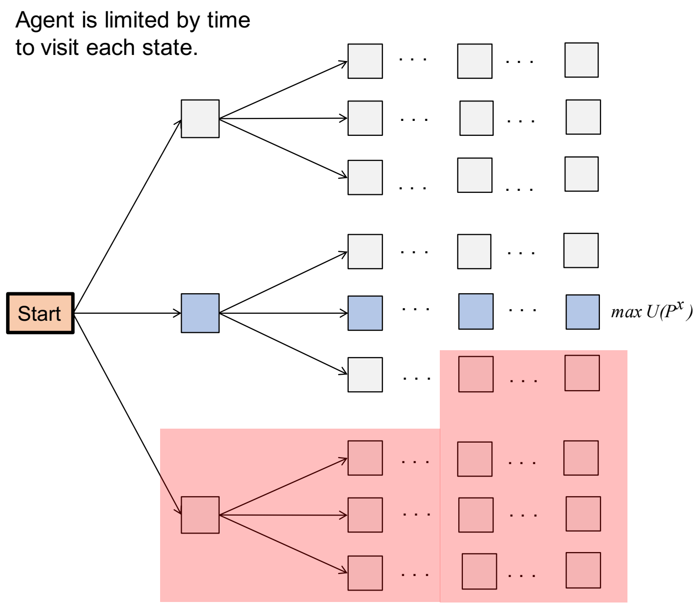


Figure 5.4: Search tree that limits the number of evaluated states in the search space to be less than $BR\text{-}A(T)$, with a depth-first search

In STRIPS-BR, the time bound limits the number of states in the search space during the construction of a search tree. A search tree constructed by a time-bound agent is illustrated in Figure 5.4. The covered states are not accessible to the agent as search time has run out. Goal-directed heuristics like those used by STRIPS and STRIPS-BR begin by searching for actions to satisfy the first goals encountered. Hence, to overcome the time bound $BR\text{-}A(T)$, it makes sense to order goals in a way that "best" plans tend to show up first in the search process before running out of computational time. Here, the importance of the practical goal order $rank(x, s_i)$ captured by the outcome O^x of a plan provides important and observable insights.

A practical initial order ensures a viable plan is found within the available time. Without action preconditions, it would be sufficient to place preferred goals at the beginning of the initial goal list $G\text{-}BR_0$ at time step $t = 0$. However, due to action preconditions, certain goals may be satisfied out of order, placing preferred goals at the end of the plan. Balancing the practical order and an agent's preferred order within limited search time is the focus of the next section.

[2] A Turing machine is a theoretical model of a computer, first devised by Alan Turing in 1948

5.5 Goal Ordering in Planning

Goal ranking imposes some order on a set of goals. For STRIPS-BR to construct a search tree and calculate the utility of a plan, four goal orderings are required: the initial goal order to initialize the planning process, the final order of satisfied goals after plan execution, and two independent orderings to calculate utility of a plan during plan generation and execution phases.

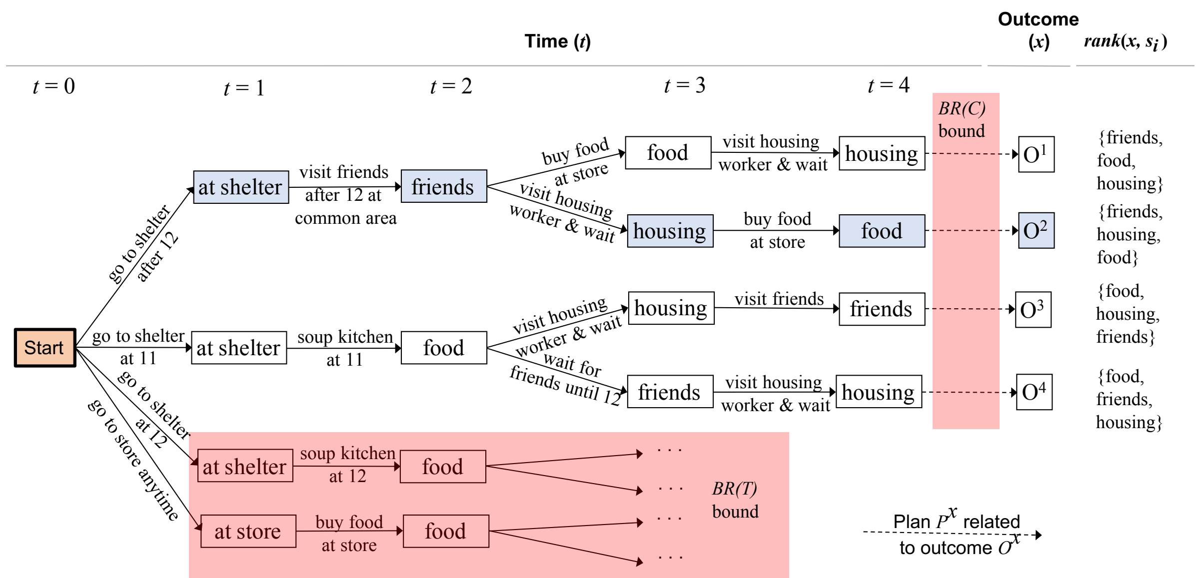


Figure 5.5: Homeless agent decision tree example from Section 4.3.1.

To demonstrate the role each ordering plays in the AI planning process, consider again the agent in Section 4.3.1 but this time with a search tree constructed with STRIPS-BR as in Figure 5.5. Rather than capturing all plans considered "reasonable" by the observer, each plan included in the tree is based on the initial order, action preconditions, and the agent's bounds. The agent's goals are mapped to MH levels, where "food" is a physiological goal, "housing" is a security goal, and "friends" is a social goal. These are satisfied by visiting the soup kitchen (physiological), reserving a bed at a shelter (security), and visiting its friends at a community centre (social). Some actions have preconditions that must be satisfied first. These include the subgoals of being "at shelter," "at store," or "at street."

Initial Goal Order

The planning process begins with the construction of a search tree using the initial goal order $\{friends, food, housing\}$ at time step $t = 0$. The STRIPS-BR reasoner selects actions that satisfy goals in this order according to the action selection heuristic introduced in Section 4.3.3. Without utility maximization, an agent could simply select the first possible plan generated using the initial order within its bounds. For the example search tree in Figure 5.5, the agent would choose plan P^1 with outcome O^1 where the final goal ranking $rank(1, s_i)$ matches goal order in $\{friends, food, housing\}$.

Agent-Preferred Goal Order

The agent's preferred order represents the order in which the agent would like to satisfy its goals. It is independent of any other orderings or constraints. It is assumed that this ordering, labelled as *pref* = A with ranking $rank(A, s_i)$, is the order in which goals are expressed by an agent. For example, a homeless client may express requests to a service provider in the client's preferred order. Hence, this may represent their true preferences or learned preferences based on previously observed or executed plans. Without information to the contrary, an agent's preferred order is assumed to be the initial order used for planning. If all preconditions are met for required actions, an observer may infer that the first plan P^1 and its outcome O^1 indicates the agent's preferred order. Here, the agent's preferred order, identified by *pref* = A, orders goals in the same order as the outcome O^1 identified by *pref* = 1, where for all goals s_i satisfied by P^1, $rank(A, s_i) = rank(1, s_i)$.

During the plan generation phase, the agent is assumed to be rational in the neoclassical sense and to know all information required to make a plan. As a result, the order they choose is one they believe is their preferred order for a given scenario. Hence, during the plan generation phase plan utility is calculated using *pref* = A. Selecting a plan with maximum plan utility calculated using $rank(A, s_i)$ ensures a selection that best suits the agent's preferences.

Practical Goal Order

The "practical" order is imposed on the planning process by the agent's constraints as well as the preconditions and postconditions of actions an agent chooses. This order is the final goal order of *satisfied* goals in $G\text{-}BR_k^S$ after a plan P^x was successfully executed at time step $t = k$, namely $rank(x, s_i)$ where $s_i \in G\text{-}BR_k^S$. If action preconditions were satisfied at each time step, the final order would simply be the initial order with no need to find other plans. If preconditions are not yet satisfied, the goal order is determined by the executable order in which actions satisfy goals. This order ensures that any actions required to satisfy preconditions of other actions are executed first. A search tree is constructed in such a way to only include such plans, within the agent's bounds. Given the example in Figure 5.5, the search tree includes possible plans P^1, P^2, P^3, and P^4, along with their associated outcomes O^1, O^2, O^3, and O^4. Each outcome has a different "practical" order of satisfied goals with rankings $rank(x, s_i)$, where $x \in \{1, 2, 3, 4\}$.

After executing a set of plans, over time an agent may be able to identify which practical order is best and adopt it as its preferred or initial order. For example, an agent may have executed plan P^3, deferring staying with friends until the end. It is possible that the appointment with a housing worker took the rest of the day, and they could not meet with their friends at time step $t = 4$. However, if, after executing plan P^4 once, they realize that they can meet with friends before visiting the housing worker, they could simply have the practical goal order for O^4 be their initial order, where $rank(4, s_i)$ produces $\{food, friends, housing\}$. In this case, the agent's initial order is now equal to the practical order of plan P^4, where $rank(A, s_i) = rank(4, s_i)$ for all $s_i \in G\text{-}BR$. By initializing the search tree construction process with a practical goal order, it is more likely that a plan is found within the time bound of the agent, since at the very least, one of the first plans will be a previously executed plan that resulted in the practical goal order. Consider a situation where the initial order is very different from the practical order. If a given *AS-BR* contains actions that satisfy goals in a different order than the initial order, the STRIPS-BR planner may go through a large number of nodes looking for plans. If the plans that match the initial stage are further along in the search tree, the STRIPS-BR planning process may not reach them within the agent's time bound. Hence, an initial order that is similar to a practical order will use less of the agent's cognitive resources. Finally, by choosing a practical order as the initial order, it can be said that, at least for efficiency, an agent may prefer this order over all others. This is especially important at times of emergencies when an agent must make quick decisions and spend less time searching for a plan. Aligning the initial order with the practical order will allow the agent to respond to such situations quickly.

Maslow's Goal Ordering

Similarly to the preferred order during the plan generation phase, Maslow's order is used during the execution phase. This is based on the assumption that during execution, regardless of what the agent's preferred order is, Maslow's order will reflect their realistic needs. For example, recall from Section 3.4.2 that the utility $u(pref, s_i)$ in Equation 3.17 with $pref = MH$ considers Maslow's original order to calculate goal utility in relation to the lowest MH level outstanding. A higher utility is calculated for a particular sequence if it satisfies goals in an order similar to Maslow's original ordering, where each goal $s_i \in G\text{-}BR$ is ranked with $rank(MH, s_i)$. For the example agent presented here, the planning process would be initialized with goal order $\{dinner, bed, friends\}$ for physiological, security, and social goals related with $\succ_{MH}$.

Hence, during execution, $pref = MH$ is used to calculate plan utility. An agent's preferred preference $pref = A$ during the plan generation phase may differ significantly from MH. Both orders may differ from any practical order $pref = x$. This may cause a large difference in plan utility calculated during the plan generation and execution phases; so much so that the agent may need to abandon its plan altogether and find a new course of action. In AI planning this is called replanning, and will be discussed further in Section 5.6.

Cardinal Utility for Interim Goals

Not all goals in a plan are basic human needs that can be mapped to Maslow's levels. Some are interim goals, as introduced in Section 4.3.3. The goal-driven heuristic used by STRIPS-BR ensures that a selected action's preconditions are added to $G\text{-}BR_t^U$ as goal propositions. Such propositions may not be associated with any MH level, but serve simply as a subgoal to allow the action to be executable. Such goals and actions are called "interim goals" and "interim actions." Interim actions are considered costs and have a constant negative weight of −0.01, as per Equation 5.2.

$$u(execu, pref, a_t^x) = -0.01, \tag{5.2}$$

where a_t^x is an interim action (so $pref$ is ignored), and $execu \in \{exp, ecoc\}$.For example, eating a hot meal at the soup kitchen satisfies the physiological need to reduce hunger. The precondition of being at the soup kitchen at the appropriate time is an interim goal. Travelling to the soup kitchen is an interim action. A negative utility ensures that interim goals and actions are minimized in a plan that maximizes plan utility.

5.6 Plan Execution Phase

Once an agent selects a plan, plan execution begins. During plan execution, an agent must adapt to a dynamic environment. A BRAMA agent triggers the replanning process using an emotional threshold. Once triggered, goals are reranked and the utility of a new plan is calculated. The result is a combination of resolute and sophisticated strategies being deployed when required by the agent. The myopic strategy is deployed if $BR\text{-}A(C) = 1$, as per Section 5.4.2. During plan execution, the agent begins with the resolute strategy. Once the threshold is reached, the agent must stop and recalculate its utility moving forward, similarly to the sophisticated and myopic strategies.

The plan is executed one action at a time, with plan utility being recalculated at each time step. Environmental feedback reflects similarities and discrepancies between $AS\text{-}BR$ (assumed by the agent) and $AS\text{-}cor$ (representing reality), and likewise between $S\text{-}BR$ and S_t. For example, if a to-be executed action $a_t^x \in AS\text{-}cor$, it will be executed as planned. However, if $a_t^x \in AS\text{-}inc$, or some proposition $s_i \in S_t$ but $s_i \notin S\text{-}BR$, the execution will fail. In this case, either the action's preconditions will not be satisfied or the add-propositions will not satisfy the intended goals in $G\text{-}BR_t^U$.

The agent may also evaluate the importance of certain actions and goals differently during the plan generation and execution phases. For example, while initially focusing on social goals and meeting friends, the agent may become anxious about not securing a bed for the night. The plan with highest utility based on the agent's preferred ranking $rank(A, s_i)$ has social goals ranked higher than security goals. If the agent did not anticipate being nervous about securing a bed, and Maslow's order is a more objective order than the agent's preferred order, as discussed in Section 2.6.1, it can be used to evaluate utility during the execution phase instead of the agent's preferred order. Hence, when the agent uses Maslow's $rank(MH, s_i)$ ranking, securing a bed becomes more important than meeting friends.

5.6.1 Plan Monitoring with ECOC

During the execution phase the agent is actively monitoring plan execution by evaluating plan utility at each time step. Unlike the plan generation phase, expected utility during the execution phase is not strictly based on neoclassical utility $exp(t)$. Instead, the agent model $\mathbb{M}$ uses $execu$ to define which expected utility function is used, where $execu \in \{exp, ecoc\}$. This represents how realistic the agent is about its abilities. If the agent was realistic, expected utility during planning is the same as during execution, namely $exp(t)$. In this case, the agent is well informed about its abilities and exhibits increasingly optimistic progress towards its goals. However, if the agent was not realistic during planning, its utility during execution is based on $ecoc(x)$. In this case, the agent was overly optimistic about its abilities during the plan generation phase. The differences between plan generation and execution phases become apparent as the $exp(t)$-based utility during planning deviates from $ecoc(x)$-based utility during execution. Here, the emotional response to the agent's performance is revealed under true consequences of their actions.

To adapt to such differences between planned and executed actions, the agent recalculates utility and replans its actions when needed. Recall that axiom BR-8 states that when a change to a plan is sufficiently large, it will cause a reranking of goals. Hence, if the discrepancies between planned and executed actions become sufficiently large for any of the reasons listed, the agent will stop execution to reevaluate its situation. While it would be unrealistic to replicate the exact thought process and goal reevaluation of an individual, it is possible to categorize observed responses of an agent as optimistic or pessimistic, and emulate how that affects goal reranking. For example, consider an agent that ranks social goals as most important and physiological goals as less important, captured by $rank(A, s_i)$. Goal utility during the execution phase, which relies on Maslow's original order with $rank(MH, s_i)$, will be calculated lower than during planning.

In BRAMA, axiom BR-8 is represented by a replanning trigger based on emotional stage of the agent, not present in sequential DT. It allows a BRAMA agent to dynamically adjust which decision strategies are used based on how low plan utility has become during a pessimistic stage. For standard myopic and sophisticated strategies, replanning occurs at each time step when available sequences are reevaluated and a new sequence utility is calculated. For the resolute strategy, no such functionality is provided. Neoclassical expected utility does not provide variability in the calculated utility for a rational agent, as it always improves. In BRAMA, the emotional cycle of change provides the ability to trigger such a process by introducing a new emotional threshold, extending the fidelity of the BRAMA agent model.

5.6.2 Replanning with ECOC

Recall that the ECOC, calculated by the $ecoc(x)$ function, provides five stages that transition the agent from a stage of uninformed optimism through the pessimistic valley of despair, eventually moving through informed optimism towards success. This is in contrast to the always optimistic neoclassical expected utility, calculated by the $exp(t)$ function. The $U(execu, pref, P_t^x)$ plan utility function across time steps t is presented in Figure 5.6. Unlike the primarily monotonically increasing $exp(t)$, the non-monotonic $ecoc(x)$ exhibits fluctuations that cause the agent to act optimistically (upwards direction) or pessimistically (downwards direction) about the expected success of their plan. Moving from an optimistic to a pessimistic mood will cause the agent to reevaluate its situation. Once reevaluated, a new course of action can be selected by generating a new plan. BRAMA introduces the *ecoc-th* threshold used to monitor plan utility during execution that can trigger this replanning process.

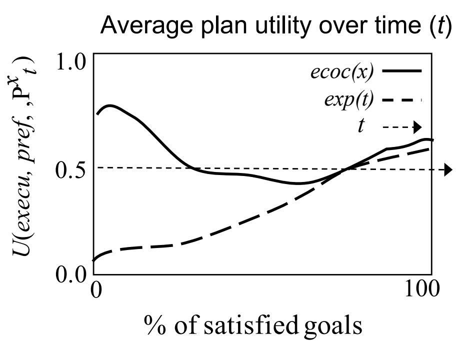


Figure 5.6: Comparison of $U(execu, pref, P_t^x)$ for $exp(t)$ versus $ecoc(x)$

The *ecoc-th* threshold represents an emotional limit an agent can handle before pausing and reevaluating its plan. If at time step t plan utility $U(execu, pref, P_t^x) < ecoc\text{-}th$, plan execution halts and the replanning process begins. A lower *ecoc-th* indicates a more resilient agent that can withstand a lower emotional mood before replanning. In the context of decision theory, an agent with a low *ecoc-th* is said to use a *resolute* strategy, since it does not deviate from its original plan unless it has a low *ecoc-th* value. A higher *ecoc-th* means the agent is sensitive to reductions in plan utility, halting execution and replanning sooner rather than later.

Once execution stops, the agent begins to identify which goals to retain or defer. The agent considers the utility of individual actions in the plan, where *action-th* is the threshold that controls what actions remain. Figure 5.7 illustrates the pattern of $u(execu, pref, a_t^x)$ using $exp(t)$ and $ecoc(x)$ over time steps t. If $u(execu, pref, a_t^x) < action\text{-}th$, the action is removed and any goals the action satisfies are deferred until a later time. In the next cycle, a plan to satisfy only the retained goals is generated. The deferred goals are retrieved only once retained goals are satisfied.

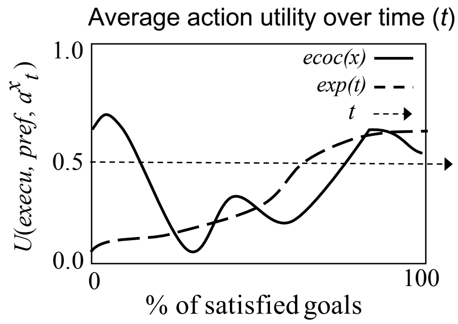


Figure 5.7: Comparison of $u(execu, pref, a_t^x)$ for $exp(t)$ versus $ecoc(x)$

5.7 Agent Replanning and Simulation

An important part of replicating a bounded agent's plan generation and monitoring is the environment that forces the agent to reevaluate its plan during plan execution. This section introduces the BRAMA simulation environment that controls these tasks. As an agent's plan is executed, plan monitoring evaluates the "true" plan utility. A substantial difference between the planned and "true" utilities triggers the replanning process. BRAMA incorporates a discrete-event simulation, a popular simulation architecture for bounded agents in social sciences [123, 106]. In such a simulation, the execution of complex systems is represented as an ordered sequence of events. Using forward chaining, an action is executed as a discrete event at time step t, rather than continuously over time. The actual time taken between each event may vary in length.

In BRAMA, each executed plan, whether partially or completely executed, represents a cycle in the life of the agent. For a "homeless" agent, the cycle may be a 24-hour period in which it must carry out tasks to satisfy as many goals as it can. The goals satisfied by the executed portion of a plan are not included in plan generation during future cycles. The agent is assumed to have mastered these tasks and can execute them without planning. While this plan-reuse resembles case-based approaches, portions of plans are not reasoned about explicitly, as in case-based planning architectures [147]. Instead, a brand new plan is generated for retained goals. Once a partially executed plan is complete, the current cycle ends. At the beginning of the next cycle, the agent retrieves deferred goals and generates a new plan. The time between cycles is also domain or situation specific. For example, a real individual may take one day, week, or a month to move from one cycle to another. To an agent, an emulated cycle lasts only one iteration of the planning-replanning process. Matching cycles to actual time duration is addressed in the evaluation of the model in Chapter 7.

5.7.1 BRAMA Agent Model

The BRAMA agent model $\mathbb{M}$ provides properties used to define an agent that generates and monitors plans while the simulation executes them and recalculates utility, as listed in Table 5.3. The structure

$$\begin{aligned}\mathbb{M} = \{&demo(), BR\text{-}A(I), BR\text{-}A(C), BR\text{-}A(T),\\ &execu, G_0, strategy, pref, planu, ecoc\text{-}th, action\text{-}th\}\end{aligned} \tag{5.3}$$

Table 5.3: BRAMA agent model that interact with the simulation environment

Variable	**Description**	**Value/Source**
$BR\text{-}A(I)$	Bounded rationality assignment for limited knowledge (I).	$I = \{S\text{-}BR, G\text{-}BR, AS\text{-}BR\}$, *a priori* or data
$BR\text{-}A(C)$	Bounded rationality assignment for limited cognition (C).	$C \in \mathbb{Z}$, *a priori* or data
$BR\text{-}A(T)$	Bounded rationality assignment for limited computation time (T).	$T \in \mathbb{Z}$, *a priori* or data
$exp(t)$	Neoclassical expected utility function.	Equation 3.18
$ecoc(x)$	ECOC expected utility function.	ECOC Equation 3.19
execu	Expected utility function used during the plan generation phase.	*exp* or *ecoc*
ecoc-th	ECOC threshold.	$ecoc\text{-}th \in [0, 1]$
action-th	Action threshold.	$action\text{-}th \in [0, 1]$
AS-cor	Correct action schema.	*a priori* or data
AS-BR	Agent's bounded action schema.	*a priori* or data
MH	Mapping relations between an agent's goals and Maslow's hierarchy.	*a priori* or data
pref	The ordering for a set of goals, where $pref \in \{A, MH, x\}$ for the agent's preferred order, Maslow's order, and practical order after execution of sequence A^x and outcome O^x.	A from *a priori*, MH from a mapping of goal to Maslow levels, O^x from a run trace.
$demo()$	Agent demographics or characteristics.	*a priori* or data
$S\text{-}BR_0$	Initial state of the world at time step $t = 0$, available to the agent.	*a priori* or data
strategy	Decision strategy used by the agent.	*myopic*, *sophisticated*, or *resolute*
planu	Plan selection used.	*none*, *noneswap*, *planu*, *planutilswap*

represents a particular type of individual and his or her characteristics. The function $demo()$ categorizes the agent as a member of some cohort within a population based on its demographics, such as age, gender, or income. Demographics are not used as part of the simulation directly. Instead, demographics are used to group agents into a representative cohort for a particular domain-specific population. A cohort, then, is represented by some $\mathbb{M}$ configuration. The agent's bounds $(BR\text{-}A(I), BR\text{-}A(C), BR\text{-}A(T))$ indicate its cognitive limitation during the plan generation process. Its expected utility function during plan generation is $exp(t)$ as the agent is assumed to be rational and maximizes its utility. The agent's initial goals at time step $t = 0$ are G_0, and goal utility is based on the agent's own goal preferences ($pref = A$). The agent can be configured to use one of the three decision strategies from dynamic choice theory, namely myopic, sophisticated, or resolute.

During the execution phase, the utility function (*execu*) can be either $exp(t)$ or $ecoc(x)$. The agent can also be configured to use its preferred ranking ($pref = A$) or Maslow's ranking ($pref = MH$). It can either maximize its utility ($planutil = planutilswap$) or not ($planutil = none$). Finally, to trigger the replanning process, the agent has two thresholds *ecoc-th* and *action-th*, as discussed in the next section.

5.7.2 BRAMA Simulation Environment

The simulation environment controls when plan generation, monitoring, and execution occur with several modules that perform specific functions, as listed in Table 5.4. The simulation process begins with $simulate(S_t, G_t)$, which takes two parameters, the current state of the world S_t and the agent's goals

G_t at time step t. At the start of the simulation, $S\text{-}BR_t$ and $G\text{-}BR_t$ are used to initialize the process. The procedure returns a set of partial plans that were executed and the resulting world state, PL_{Final} and S_{Final} respectively. Another module, $plan(S\text{-}BR_t, G\text{-}BR_t, AS\text{-}BR)$, generates a plan P_t^x using STRIPS-BR. The third parameter $AS\text{-}BR$ ensures the plan is generated using the agent's bounded action schema in $BR\text{-}A(I)$. The function $next\_action(P_t^x)$ returns the next action a_t^x in plan P^x to be executed. The action must be a correct action in $AS\text{-}cor$ to ensure realistic preconditions and postconditions are enforced on the agent during the execution phase. To ensure it is correct, the inverse of Equation 3.2 is used, namely $a_t^x = inc^-(a_t^{*x})$ where $a_t^x \in AS\text{-}cor$ whether a_t^{*x} is in $AS\text{-}cor$ or not. Next, the procedure $exec(a_t^x, S_t, G_t)$ executes the action, given the agent's current unsatisfied goals in G_t and the true current state S_t. During execution it transitions the state S_t to the new state S_{t+1}.

Table 5.4: Simulation environment modules

Module	**Descriptions**
G_t	Unsatisfied goal propositions at time step t.
G_0	Initial set of unsatisfied goal propositions at time step $t = 0$.
$simulate(S_t, G_t,)$	Begins the simulation process.
$plan(S_t, G_t, AS\text{-}BR)$	Finds a plan P_t^x using the STRIPS-BR planner.
$next\_action(P^x)$	Returns the next action a_t^x in plan P^x.
$exec(a_t^x, S_t, G_t)$	Executes the action a_t^x, given state S_t and goals G_t. Returns the new state S_{t+1}
$retain(G_t)$	Returns a reduced set of goals G_R that will be used for replanning, as per Equation 5.4.

The agent monitors plan execution by comparing plan utility $U(execu, pref, P_t^x)$ to the *ecoc-th* threshold. If the utility is above the threshold, execution continues. If the utility falls below the threshold the replanning process is triggered. During the replanning process, $G_R = retain(G_t)$ returns a subset of goals in G_t to be used in planning. For each remaining goal proposition s_i at time step t, where $s_i \in G_t \cap G_0$, and each action $a_t^x \in P_t^x$ that satisfies that goal proposition s_i, $G_R = retain(G_t)$ returns a subset of goal propositions in G_t that remain after other goals were deferred, as defined in Equation 5.4. For an action a_t^x in plan P^x being executed at time step t,

$$G_R = retain(G_t) : \{s_i \in G_t \cap G_0 \mid s_i \in ADD_t^x \wedge U(execu, pref, a_t^x) \geq action\text{-}th\} \tag{5.4}$$

where $s_i \in ADD_t^x$ for each goal proposition $s_i \in G_t \cup G\text{-}BR$ and each action $a_t^x \in P_t^x$ that satisfies that goal. The subset of original goals in $G\text{-}BR$ (excluding interim goals) still not satisfied are returned and stored in the goal set G_R, and used to generate a new plan.

Figure 5.8 presents the simulation flowchart, which relies on properties of the agent model $\mathbb{M}$ to control how the agent interacts with the external world. The simulation environment attributes and modules are listed in Tables 5.4 and 5.5. If the agent is configured to evaluate plan utility during execution using ECOC then $execu = ecoc$ and the simulation may trigger the replanning process.

Once a plan is generated and plan execution begins, plan utility is recalculated at each time step t. While monitoring execution, the agent compares the new utility to its *ecoc-th* threshold. If

$$U(ecoc, pref, P_t^x) \geq ecoc\text{-}th,$$

plan execution continues at time step $t = t+1$. Otherwise, goals are retained in G_R, where $G_R =$

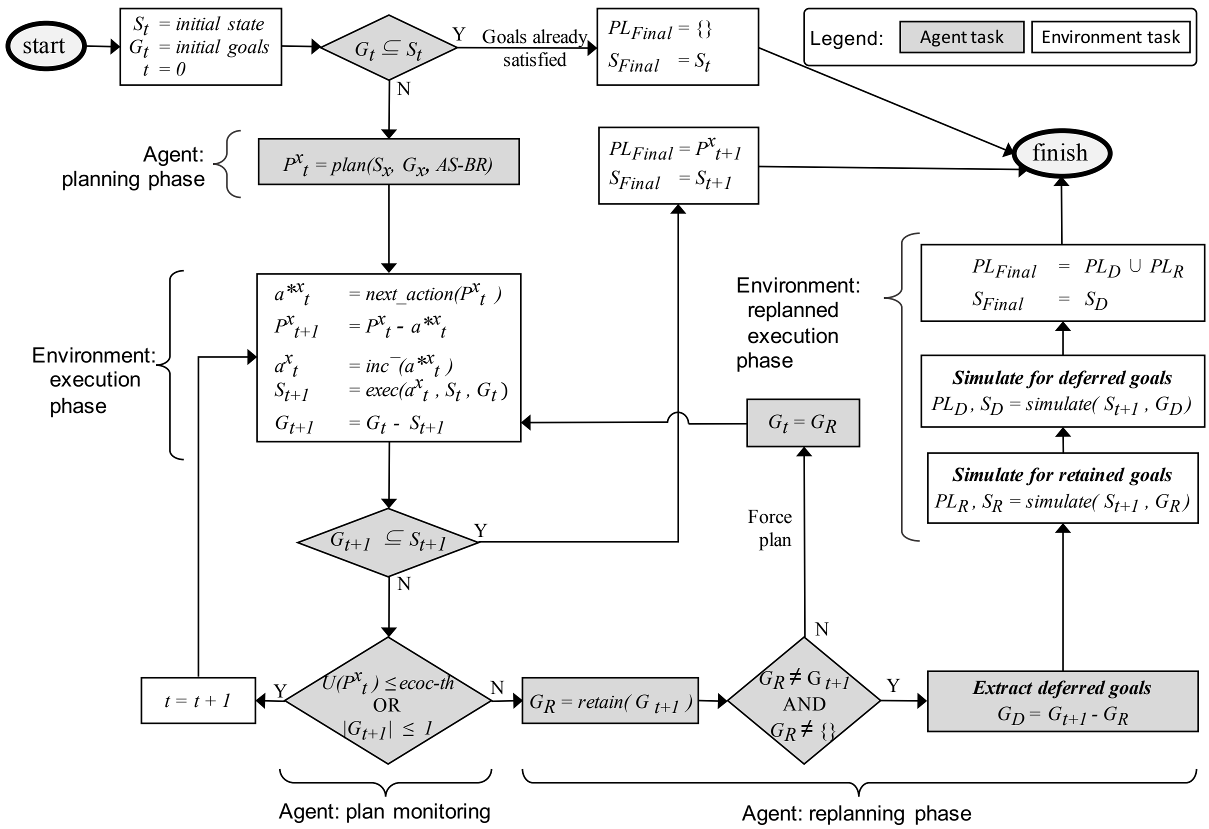


Figure 5.8: Agent simulation flowchart

Table 5.5: Attributes of the BRAMA simulation environment

Attribute	**Descriptions**
t	Simulation time unit.
S_t	Correct state of the world at time step t.
G_t	Agent goals at time step t, where $G_t \subseteq G\text{-}BR^U$.
P^x	Plan at index x.
P^x_t	Partial plan P^x from start to time step t.
a^x_t	Current action being executed.
G_R	Reduced goals, where $G_R = retain(G_t)$, as per Equation 5.4.
G_D	Deferred goals, where $G_D = G_t - G_R$.
S_R	State of the world after reduced goals are satisfied.
S_D	State of the world after deferred goals are satisfied.
PL_R	Set of plans after reduced goals are satisfied.
PL_D	Set of plans after deferred goals are satisfied.
S_{Final}	Final state of the world, returned by $simulate()$.
PL_{Final}	Final set of plans, returned by $simulate()$.

$retain(G_t)$ according to the agent's *action-th* threshold, as per Equation 5.4. The deferred goals are added to the set G_D. If $U(ecoc, pref, P^x) < ecoc\text{-}th$ but either no goals can be removed or all goals are removed, a new forced plan is created and executed without considering *ecoc-th*. Any goals satisfied by a "forced" plan are accumulated for all forced plans in one cycle. If a "forced" plan cannot satisfy its goals it becomes a "failed" plan. Goals of a "failed" plan persist until they are satisfied after replanning or remain until the end of the simulation. After a "forced" plan completes or becomes a "failed" plan, the agent generates a new plan for the remaining goals. This plan's initial state of the world and goals are carried over from the previous time step, where $U(ecoc, pref, P_x) > ecoc\text{-}th$. The cycle continues until all goals are satisfied or the current plan fails.

Once retained goals are successfully satisfied, the state of the world is represented as S_R and the set of plans required to satisfy retained goals is PL_R. The simulation is executed again for all deferred goals G_D starting at state S_R. Once deferred goals are retrieved and satisfied, the state of the world is represented as S_D and the set of plans required to satisfy all deferred goals is PL_D. The simulation ends when all retained and deferred goals are satisfied. The final state of the world is S_{Final}. The set of plans used to satisfy retained and deferred goals is PL_{Final}, where $PL_{Final} = PL_D \cup PL_R$.

5.7.3 Replanning Example

Figures 5.9 to 5.11 illustrate the search trees an agent creates using STRIPS-BR, its goals, and how the replanning process reranks them. Consider again the "homeless" agent introduced previously whose goals are to obtain food (physiological), meet with friends (social), and meet a housing worker (security). Some actions have preconditions that must be satisfied first. These include the subgoals of being "at shelter," "at store," or "at street." The preferred order is $\{friends, housing, food\}$. To achieve its goals, the agent creates a search tree with several plans to satisfy them. According to the correct action schema *AS-cor*, food can be obtained by going to the shelter when the local soup kitchen is open at 11:00 or 12:00. An agent can also purchase food at the store any time at a cost of \$10.00 and panhandle for more money. The agent can visit friends after the 12:00 lunch at the common area where clients socialize. Finally, it can book an appointment with a housing worker and wait until it is called for an appointment. The agent's bounded action schema *AS-BR* is a subset of $AS\text{-}cor \cup AS\text{-}inc$. In *AS-inc*, food costs \$3.00, which the agent believes, rather than the true cost of \$10.00, as defined in *AS-cor*.

Step 1: Planning

In Figure 5.9, the agent begins the planning process in the "Start" node at time step $t = 0$. With a cognitive bound of $BR\text{-}A(C) = 4$ the agent can look four steps ahead. Each action transitions the agent into a new state in the search space at time steps $t = 1, \ldots, 4$. Each plan leads to an outcome O^x, with a practical order of goals where $pref = x$ and ranked with $rank(x, s_i)$. With $BR\text{-}A(T) = 24$ the agent does not see past the first 24 states in the search tree, omitting the last two paths that begin with a visit to the housing worker and panhandling. Note that panhandling is not part of any of the other available paths as that would require looking five time steps ahead, which is not possible due to the $BR\text{-}A(C) = 4$ limit.

After calculating the utility of each plan using $exp(t)$ and $pref = A$, the agent chooses plan P^2 as having the highest utility. Using a resolute strategy, the agent's intention is to follow plan P^2 to the end. Its practical order and the inferred preferred order seem to be $\{friends, housing, food\}$.

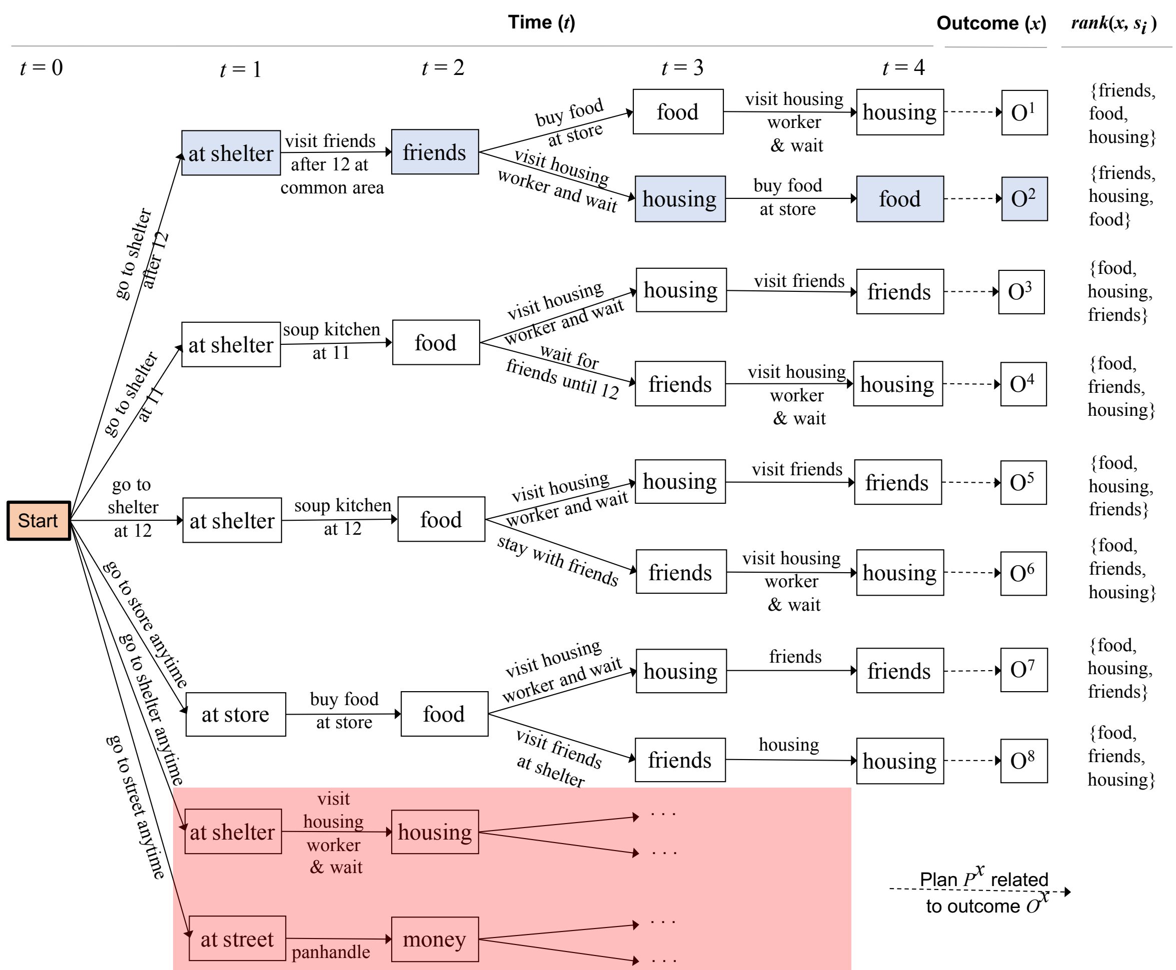


Figure 5.9: First search tree starting at time step $t = 0$, and selected plan P^2

Step 2: Execute Original Plan

During execution, the agent meets with friends at time step $t = 2$ with the intention of next visiting the housing agent to secure housing, then going to the store to buy food. Once at time step $t = 2$, however, the plan is reevaluated using Maslow's ordering (where $pref = MH$) and the $ecoc(x)$ expected utility function. Since housing (security) is ranked lower than food (physiological) according to MH ranking $\succ_{mh}$ but not according the preferred ranking $\succ_A$, the agent prefers to obtain food over visiting the housing worker. Knowing it will only have one meal today, it becomes worried about spending the entire time waiting for the housing worker without a meal beforehand. In this scenario, the utility of P^2 falls below the agent's *ecoc-th* threshold, triggering the replanning process.

Step 3: Replanning

The replanning process begins by identifying the actions for which $U(execu, pref, a_t^x) < action\text{-}th$, and deferring any goals they satisfy. Housing is less important than food in Maslow's order and, say, utility of a "housing" action falls below the threshold, hence *housing* is deferred. A new search tree is constructed for the remaining goal, $food$. The agent knows that it is too late for visiting the soup kitchen, as it is after 12:00. There are only two possible plans for which preconditions are true in $S\text{-}BR_2$ at time step $t = 2$ in Figure 5.10. The first is plan P^{11} where the agent buys a sandwich at the store for \$3.00 with the \$5.00 the agent has. The second is plan P^{12} in which the agent first panhandles for more money then purchases a sandwich at the store. Believing it has enough money for a sandwich and having low expectation of making any money panhandling, the highest utility is calculated for plan P^{11}, which is chosen, as depicted in Figure 5.10.

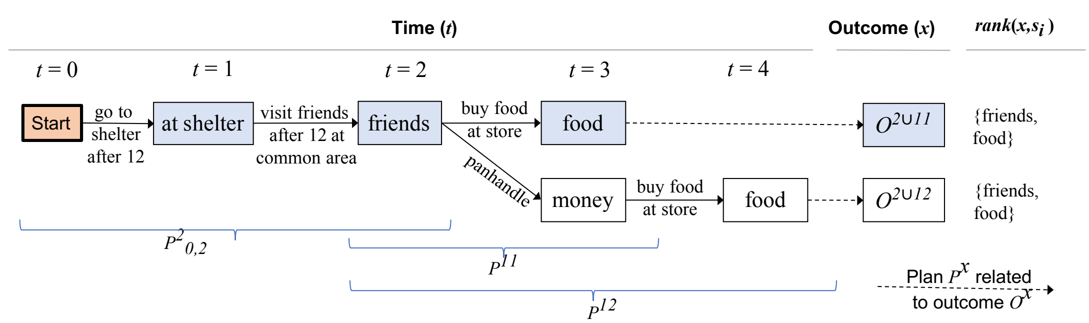


Figure 5.10: Second search tree after replanning, starting at time step $t = 2$, and selected plan $P^{2\cup 11}$

Starting at time step $t = 2$, the agent chooses plan P^{11} with outcome O^{11} for execution. Taking the union of the partially executed plan $P^2_{0,1}$ and the new plan P^{11} we get $P^{2\cup 11}$, as per axiom BR-9 for an observable plan. This new plan imposes a new practical order in $O^{2\cup 11}$ at time step $t = 3$ where $rank((2 \cup 11), s_i)$ gives $\{friends, food\}$. In the new order, the already satisfied goal $friends$ remains first. The goal $food$ is moved up from the third place in P^2 to the second place in plan $P^{2\cup 11}$. The goal for *housing* is deferred, and not included in outcome $O^{2\cup 11}$.

Step 4: Execute New Plan

During execution of $P^{2\cup 11}$, the agent learns the true cost of food at the store is \$10.00, not \$3.00. The agent now tries to overcome this precondition to determine whether it is a weak or strong precondition.

As described in Section 5.7.1, the agent tries a "forced" plan execution that ignores *ecoc-th*. However, the precondition is a hard requirement, and the agent has no immediate actions that allow it to purchase food. Plan $P^{2\cup 11}$ is deemed a "failed" plan, but the agent can try another plan. For example, the agent tries plan P^{12} available to it, to panhandle first then purchase the sandwich, as illustrated in Figure 5.10. Despite initially lowered expectations, the agent successfully makes enough money to buy a sandwich at time step $t = 4$ for \$10.00, concluding execution of the plan $P^{2\cup 12}$ with outcome $O^{2\cup 12}$.

Step 5: Plan Generation and Execution for Deferred Goals

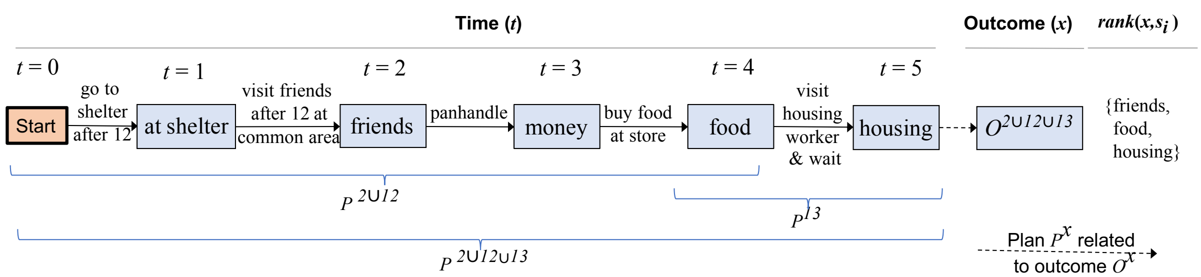


Figure 5.11: Third search tree after replanning, starting at time step $t = 4$, and selected sub-plan P^{13}, producing the final plan $PL_{Final} = P^{2\cup 11\cup 13}$ and outcome $O^{2\cup 12\cup 13}$

Once the $friends$ and $food$ goals have been achieved, deferred goals are retrieved and added to G_t. For this example, the *housing* goal is retrieved at time step $t = 4$. A new plan is created and executed, adding the new action of visiting the housing worker and waiting for the appointment. Figure 5.11 illustrates the new plan P^{13} and how it extends the previous plan $P^{2\cup 12}$. The result is a new plan $P^{2\cup 12\cup 13}$. The simulation assumes the appointment is successful with 100% probability once the agent decides to wait. Hence, after execution at time step $t = 5$, the agent successfully satisfies all goals in $G\text{-}BR_t^U$. Alternatively, the agent's success in executing the action could depend on the availability of the housing worker before the day is finished with some probability. However probabilities for success fall outside the scope of this thesis.

The final plan is a union of all partially executed plans the agent actually executed and were observable, as per axiom BR-9, resulting[3] in plan $P^{2\cup 12\cup 13}$, stored in PL_{Final}. The final goal order is $\{friends, food, housing\}$ at time step $t = 5$. Through replanning, goals were reranked from the original order $[friends, housing, food]$ the agent had preferred. The resulting final practical ranking $rank((2\cup 12\cup 13), s_i)$ gives $\{friends, food, housing\}$ at time step $t = 5$ for outcome $O^{2\cup 12\cup 13}$.

5.8 Discussion

The main thesis of the work presented here has been that seemingly irrational human behaviour can be emulated with the use of a rational reasoner. The roles that the observer and subject play in interpreting behaviour as rational or irrational have been modelled in Chapters 3 and 4 within the framework of single and sequential decision theories. This approach has focused on the observer's perspective of a subject's behaviour. The subject was modelled as an autonomous agent that interacts with a dynamic environment. The BRAMA agent model was incrementally extended to include internal and external

[3]A resulting plan $P^{x\cup y}$ is the union of only the executed portions of plans P^x and P^y.

factors that influence an agent's decisions. These included human-centric factors like bounded rationality, human goal ranking, and emotional evaluation of planned actions.

In this chapter, the BRAMA framework was extended with AI planning to capture decision making from the agent's perspective. The extended agent model is capable of planning, replanning, and goal reranking to simulate its behaviour when interacting with a dynamic environment. The result is a high-fidelity model capable of capturing human-centric constraints with an evaluation function to select a rational plan within those constraints. This high-fidelity model of human behaviour includes a variety of factors that influence an agent's decisions over time.

The agent's reasoning limitations are explicitly defined, resulting in an agent that is bounded in the quantity and quality of knowledge available to it when generating and executing its plans. Due to such limitations, knowledge stored in an agent's memory about goals and actions is in various states of incompleteness, as defined in Chapter 3. The semantics of goal relations and mappings to Maslow's hierarchy provide a way of representing agent needs in an objective way. Initially based on single decision theory, the BRAMA agent model was extended using dynamic choice theory in Chapter 4 to capture behaviour over an extended period of time from the perspective of the observer. In this chapter, the BRAMA agent model was extended using AI planning to emulate how an agent reasons about goals and actions from the agent's perspective based on its bounded knowledge and cognitive resources.

During the plan generation phase, the agent relies on a practical goal ranking (executed order) as well as preferred ranking (agent's preferred order). Practical goal ranking initializes the search process with goals the agent believes align with actions it will need to perform. This ranking is assumed to have been acquired in some way in the past. Practical ordering gives the agent better chances of finding the highest-ranked plan within its bounds. Once a search tree of plans is constructed, an agent's preferred ranking is used to calculate the utility of each plan that is found. As the agent believes the plans being considered are possible, it uses a neoclassical expectation function to calculate the utility of each plan. This function assumes the agent's expectation will increase with every achieved goal. As a rational agent, the plan with the highest utility is chosen for execution.

During plan execution, any differences between the agent's bounded knowledge used to generate the plan and reality become apparent. Correct actions are imposed by a service provider by using *AS-cor* during execution. Maslow's original goal ranking is used to monitor the true utility of each goal being satisfied. This is in contrast to the use of the agent's preferred order during the plan generation phase. Finally, if the agent was realistic in the plan generation phase about its ability to execute its plan, it uses the same utility function during the plan generation and execution phases, namely $exp(t)$. However, if the agent was not realistic, it instead relies on the emotional utility function $ecoc(x)$. Here, the emotional strain on the agent becomes apparent when the utility of planned actions and executed actions diverge over time. The emotional cycle of change is used to calculate emotional expected utility, transitioning the agent between optimistic and pessimistic expectations of success. Differences in perception of success cause an agent to reevaluate its plan and trigger a replanning process. Unlike dynamic choice theory, an agent is not bound to one of the decision strategies that either replan at every time step (myopic or sophisticated) or is executed without replanning (resolute). The decision to recalculate plan utility is determined dynamically when an agent passes its emotional threshold *ecoc-th*.

By dynamically responding to the environment, a BRAMA agent can simulate a client's progress as it interacts with service providers. A discrete event simulation environment is presented that can simulate an agent's changing decisions as it interacts with its environment. The social service provider is represented as the true action schema representing services offered to the agent and constraints placed on action execution. During the simulation, the agent finds a plan it believes will satisfy its goals, begin its execution, then triggers replanning when its emotional utility falls below its emotional threshold.

5.9 Conclusion

This chapter extended the BRAMA agent model to allow for a high-fidelity representation of a rational but bounded agent interacting with a dynamic environment. The agent's behaviour may seem irrational to an observer because the observer is also bounded. The bounds imposed on the observer prevent them from capturing all possible plans, goal preferences an agent may consider, or the emotional state an agent is in. Extending BRAMA with AI planning allows the framework to capture decision making from the agent's perspective by considering all plans an agent can view within its bounds. Also, since the agent is not able to plan for every scenario, it must instead adapt and replan during plan execution at different time steps rather than rely exclusively on one of the decision strategies. Finally, a discrete event simulation algorithm is described that simulates the BRAMA agent's interaction with its environment. The simulation captures the decisions an agent plans before interacting with the service provider, and how the agent must adjust those plans when faced with real consequences of its actions during execution. The final BRAMA agent model is of high fidelity and captures the rational process an emotional agent uses to make decisions and adapt to its bounded knowledge about its environment.

The use-case for the BRAMA model is the evaluation of a social service intervention policy by emulating homeless clients as they interact with the service provider. This process requires several components that are missing from BRAMA. These include a use-case that captures real needs of social service clients, how their needs change while interacting with the services, and the services being offered. Section 2.5.5 described existing ontologies of social services that capture offered services and service provisioning from the provider's perspective. In the next chapter, an ontology of client needs is engineered that represents how services satisfy client needs at different levels of Maslow's hierarchy. Each goal is grounded in actual requests made by clients and mapped to Maslow's hierarchy using the goal semantics described in Chapter 3. The ontology captures the relations that associate these needs with services and resources provided by the intervention program. The fidelity of the BRAMA agent model is increased by capturing the agent's motivations, constraints, and service-side resources that satisfy agent needs.

Chapter 6

Ontology of Client Needs and Social Services

6.1 Introduction

This chapter proposes a new ontology called the ontology of social service needs (OSSN) that is the ontological representation of data provided by the Calgary Homeless Foundation's Housing First program (CHF-HF), focusing on client needs and services offered. This ontology is the first of its kind to focus on the social service system from the perspective of the clients. Existing ontologies described in Section 2.5.5 focus on the service provider's perspective. OSSN has been designed to be reusable for any study that captures client and service characteristics. It includes terms required to represent a high fidelity client, including their needs, constraints, and services required to satisfy their needs. The ontology engineering methodology created by Grüninger and Fox was used to create OSSN, and is briefly introduced in the next section [101].

There are many ontologies that capture social service provisioning from the provider's perspective, as discussed in Section 2.5.5. However, no ontology exists that focuses on client needs and motivations from the client's perspective. At the same time, human motivations have long been credited with influencing decision making. This creates an opportunity for social service practitioners to use a client's own motivations to promote constructive change in behaviour [35]. However, due to the unique circumstances and life experiences of homeless clients, practitioners must rely on "whatever works" to assess and modify client behaviour based on their experience working with such clients. To assess a client's current state, questionnaires such as the Service Prioritization Decision Assistance Tool (SPDAT) measure their "vulnerability index" based on past and current circumstances. Next, needs-assessment forms are administered every tree-month to asses client needs. Once a client's state and outstanding needs have been identified, techniques like motivational interviewing and acceptance and commitment therapy are used to facilitate change in their behaviour that aligns with the client's motivating factors [35].

In Chapter 5, BRAMA was extended to incorporate a higher fidelity agent behaviour model and a simulation architecture. In the BRAMA system, client needs are mapped to the BRAMA agent model. Services are mapped to the BRAMA action schema AS. The purpose of the ontology presented here is to capture the needs of clients, limited to empirical data available about progress of participants in an intervention program under evaluation. The ontology maps, categorizes, and ranks those needs relative to Maslow's hierarchy. It also identifies a summary of unsatisfied preconditions called constraints that prevent clients from satisfying those needs. Different goal mappings introduced in Section 3.4.1 and Figure 3.1 are presented, including direct, conditional, and unconditional.

OSSN provides terms and axioms that define relationships between those terms. Data in the CHF-HF dataset are represented as ground literals (instances) in the ontology. Certain demographics are mapped to configurations of $\mathbb{M}$ agent models. Goals of the participants are mapped to Maslow's needs, and associated with a model $\mathbb{M}$. Goal rankings are represented with a goal ranking type and an integer index indicating the ordering of goals. The order in which goals are satisfied in the dataset are represented as the agent's preferred ranking, since Housing First programs are, by design, self-directed and offer this. Goal ranking according to Maslow's hierarchy are represented as an MH ranking. The order in which goals are actually satisfied after clients participate with the service provider is the practical ranking. Services and resources available to the client are inferred from the types of requested captured in the CH-HF data.

In the rest of Section 6.1 the ontology engineering methodology is introduced along with the dataset being analyzed. In Section 6.2 Maslow's hierarchy is modified to better capture the need of homeless clients in the context of CHF-HF data. This modified hierarchy is the basis for the development of the needs ontology. In Section 6.3 OSSN is presented, along with design decisions and formal definitions. Sections 6.5 and 6.6 present a discussion of the material presented and a conclusion to the chapter. The complete ontology evaluation is presented in Appendix D.1.

6.1.1 Ontology Engineering

Ontology engineering is a systemic way of constructing ontological representation of a domain. According to Grüninger and Fox, an ontology is a "a formal description of entities and their properties, relationships, constraints, [and] behaviours" [101]. This section adopts their ontology engineering methodology, and introduces a set of competency questions the ontology should be able to answer. The focus is the relationship between client needs and service providers captured by HF Assessment questionnaires in Section 6.1.2.

There are four steps defined by ontology engineering for creating and evaluating an ontology. First, **motivating scenarios** are created that arise in the application domain. These provide problem scenarios that identify what data should be represented by the ontology. These include scenarios for specific clients or groups of clients. Next, **informal competency questions** are identified which the ontology should be able to answer. A specific **terminology** includes terms used to ask and answer informal competency questions. Third, an ontology is constructed that represents knowledge required to answer competency questions. The knowledge is expressed in a formal language understandable by a machine. Finally, the informal competency questions are translated into **formal competency questions** using the terminology and formal language that allow for the automation of asking and answering identified questions.

Motivating scenarios for OSSN are based on the goals for the research presented in this thesis. These include:

1. How to evaluate intervention programs in the social service space?

2. How to monitor client progress?

3. How to monitor service delivery performance?

The informal competency questions will focus on information captured by the CHF-HF dataset. The remainder of this section introduces the dataset and its important attributes. Section 6.1.5 describes the motivating scenarios in more detail. Section 6.1.6 lists the informal competency questions derived from this analysis.

6.1.2 Data: Calgary Homeless Foundation's Housing First Program

The Calgary Homeless Foundation (CHF) [1] has provided a dataset that captured information about clients as they participate in a "Housing First" (HF) intervention program administered by CHF and its partner service providers[2]. The CHF-HF dataset contains information on approximately 4,000 individual clients who participated in the HF program in Calgary from 2009 to 2015. Data continued to be collected through 2016. The information was collected using the Housing First assessment questionnaires found at the CHF website [3]. For this analysis, 2,094 participants were included between 2012 and 2015 who exited the program, successfully or unsuccessfully, within 12 months.

Participant selection process:

1. Various "intake" forms are provided every time a client comes into a shelter participating with CHF in the Calgary region.
2. Among them, the Service Prioritization Decision Assistance Tool (SPDAT) questionnaire is administered to clients in the Calgary region. SPDAT is a tool to assess a social service client's *acuity*. The answers provided by clients are self-reported with the help of service providers. These are not clinically verified.
3. A group of organization and intervention program administrators review each newly filled out SPDAT form from the Calgary region to decide whether a client is suitable for their service offering from the intervention program.
4. The HF program selects participants that have a high acuity level, indicating they are good candidates for the level of independence required by the program.

Once program participants were selected, the following HF Assessment forms were used to capture information about them in the program. The complete forms are provided in Appendix A.

1. Once a client is selected for the CHF-HF program, they are contacted and a process for finding suitable housing begins.
2. Once housing is found, the client is relocated to the new location and given the move-in assessment form: "Move-in-Assessment (v 7.27.2015)".
3. A follow-up assessment questionnaire is administered every three months: "General-HS-HF-3-60-Month-Follow-Up-Interview (v 10.16.2015)".
4. When a client exits the program, successfully or otherwise, an exit assessment form is administered: "Exit-Assessment (v 7.27.2015)".

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[1] The Calgary Homeless Foundation: *http://calgaryhomeless.com/*, accessed November 21, 2016.

[2] Please note, the analysis and findings reported in this thesis based on the Calgary Homeless Foundation's Housing First dataset (CHF-HF) do not reflect the views of the Foundation.

[3] CHF forms: *http://calgaryhomeless.com/what-we-do/oversee-hmis/user-information-tools/hmis-forms/*, accessed November 21, 2016

6.1.3 Interpreting the Basic Needs Assessment Question

Basic needs captured by the move-in and follow-up forms are interpreted as proxies for the needs CHF-HF participants are assumed to want at each three-month interval. Since the wording of the Basic Needs Assistance question is different between the move-in and follow-up forms, some assumptions must be made to represent each question response as the preferences of needs requested by the participating clients. Based on the assumptions outlined here, the move-in and follow-up questions can be interpreted as client preferences, but within the limitations of service providers.

Three conditions must be met for the move-in and follow-up Basic Needs Assistance question to reflect the client's preferences at each three-month interval: 1) the request was made by the client, 2) the request preferred by client over other requests, and 3) resources are available to meet client's request. Hence, this thesis assumes that a) a client does not receive assistance if the client doesn't ask for it and b) when the client does request assistance, it is only administered if it is available.

Basic Needs Assistance Question Wording

In terms of the different Basic Needs Assessment wordings, the move-in question asks about the needs assistance that participants require at the time they move in. The use of the word "currently" highlights the timing of the assistance. The follow-up asks what needs assistance they received in the previous three months.

- Move-in :BASIC NEEDS ASSISTANCE: What basic needs assistance do you currently require?
- Follow-up: BASIC NEEDS ASSISTANCE: What basic needs assistance have you received during the last three months?

The question now is, can we assume that the follow-up wording implies participants asked for the assistance they received during this three-month period? Or can this assumption not be made?

A possible interpretation of the two questions could be that the move-in form captures all needs participants have and will have throughout the program, while the follow-up form indicates what services they accessed to meet those needs. There is, however, a great deal of variability in what services can be delivered and in what order, in addition to the changing needs of the clients as they participate in the program. Hence, this thesis assumes that answers to the follow-up question are a combination of previously stated needs at move-in and new needs that were requested by the client in the past three months, constrained by what services were available.

Based on the wording, we assume that the move-in question represents only what the client *currently* needs. Assistance that was provided to match these requests may have been provided in the next three months, and captured in the next follow-up form. Two reasons exists why assistance may not have been provided in the first three-month period. First, the caseworker may have decided the client was not ready to receive service assistance yet. For example, if a chronically homeless person is housed, they may ask for employment training as well. However, training requires choosing a job and attending classes to learn skills required for that job. In conversation with the client, a caseworker may determine that the client does not know what job they want yet. The client may also not be ready to take instructions from a teacher or interact with other students without disruptions. In such a situation, a client's strengths might be more suited to first developing their social skills in a controlled environment. Second, resources for the requested assistance may not be available in the three-month period the request was made. Hence, the follow-up is an approximation of when the assistance was requested by the client. It only indicates in what three-month period the assistance was provided. Hence, the follow-up form is the observed order in which services were delivered.

As introduced in Section 3.2 and demonstrated in Section 5.5, BRAMA makes a distinction between a client's preference for needs and the service provider's ability to deliver assistance to meet those needs. The agent ranking captures the client's preference for receiving assistance for one basic need over another. The practical ranking captures the service provider's ability to deliver the requested service to the client. Hence the observed order of service delivery is a combination of the client's preferences based on the order in which requests are made, and the service provider's ability to deliver the services.

In order to interpret basic needs at follow-up as reflecting, at least in part, the client's preferences, the caseworker must base the case plan and schedule on the client's needs, their strengths, and promotion of the client's agenda. The Housing First program, including CHF-HF implementation, is a "person-centered" program where the plan is "defined and driven by the [client]" [40]. Caseworkers assess a client's "goals, their strengths, and current support systems," and "further explore their needs, concerns, values, and choices." Here, case managers adopt the strength model of case management that focuses on client strengths to plan services [85]. For each identified need, a primary, secondary, and tertiary service need is also identified, along with additional services. Once a case plan and schedule are created for each client, the caseworker continuously monitors and revises the plan to ensure a client's changing needs are met and resources are available downstream. Hence, the follow-up question is interpreted as a combination of client requests and client request preferences, within the availability of service resources.

Three criteria must be satisfied for a client to successfully receive services that meet their needs.

1. Client expresses a basic need, which may or may not be filled in on the form.

2. Client's *service readiness* is evaluated by a case manager and discussed with the client.

3. If a client's readiness is agreed on, resource availability is verified and designated to the client.

Once all three steps are completed, a client can receive required assistance, which is reflected on the follow-up form.

Case Plan Creation and Monitoring

To formalize the interpretation adopted by the CHF-HF program, we review the standards of practice for implementing Housing First guidelines and procedures outlined in the "Standards of Practice: Case Management for Ending Homelessness" [40]. The standards of practice consider Housing First as a "person-centered" program, and one in which the client does not need to demonstrate housing readiness. The client also dictates what basic needs they want assistance with. Caseworkers or social workers then monitor the client throughout the program, and work with the case manager to adjust the case plan according to the client's needs and the provider's available resources.

Following the interview at intake, the caseworker/social worker monitors the client's "progress towards satisfying goals and their current needs" [40]. Monitoring includes evaluating the client's "needs and preferences." For each client, a possible end date is assigned to each service goal. The client's ability to be "mindful and continuing reflection and adjustment of goals over time" is also evaluated. The caseworker communicates any changes to the case manager and revise the case plan as needed.

Client Readiness

The CHF-HF program is a semi-self-directed Housing First program, guided by the client's expressed needs, their *readiness* to receive services, and the limits of the service provider. Within the CHF-HF program, client "readiness" is interpreted in three different ways.

Housing readiness: What differentiates a Housing First program from other, service-as-usual programs is that a client does not need to demonstrate "housing readiness" before being housed, as defined by the HF philosophy that "managing homelessness through emergency shelter responses or programs designed for 'housing readiness' [is] not appropriate for ending homelessness" [40].

Readiness to disengage: The second meaning of "readiness" is in the context of evaluating whether the client is ready to exit the program. Exiting means successfully leaving the program or being transferred to another, more suitable housing arrangement. Here, a client's "readiness to disengage" is assessed as their ability for a planned discharge from the program [40].

Client readiness: The third use of the term is to capture "client readiness," a client's readiness for a service that addresses a need expressed by the client. When deciding on the schedule, "client readiness" determines which services a client can access next. At this stage, the case manager also determines the availability of resources, including specific tasks and the involvement of "other service providers that will support goal attainment" [40].

Data Evaluation: Move-in versus Follow-up Needs

The difference between needs at move-in versus follow-up were also reflected in the data. Specifically, the type of requests provided on the move-in form are not a superset of follow-up needs: participants received basic needs assistance during the follow-up periods which they did not originally request on the move-in form, having specified new needs during follow-up visits. Hence, the distinction between what the clients requested and what assistance was provided can be represented as the observable combination of client preferences (agent ranking) and service availability (practical ranking). As part of the monitoring process, the follow-up form captures the services clients received as they progress in the program. With the case manager, the client prioritizes these needs along with previously reported needs.

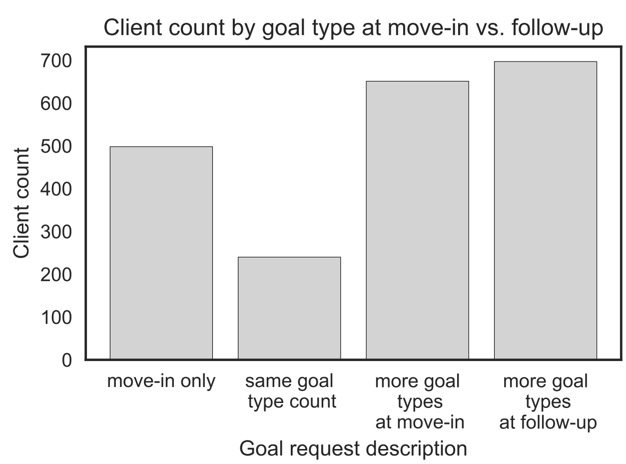

Figure 6.1: Client count by goal periods

Figure 6.1 shows the number of clients for each group of goal requests. The first category ("move-in only") consists of clients that only provided goals at move-in and then exited the program. The second category ("same goal type count") consists of clients with the same number of goal types requested at move-in as received in follow-up visits. The third category ("more goal types at move-in") consists of clients that requested more goal types at move-in than at follow-up. For this group, some goals went unsatisfied or were not reported in follow-up visits. The fourth category ("more goal types at follow-up") consists of clients who reported receiving assistance for goal types at follow-up visits that were not reported at move-in.

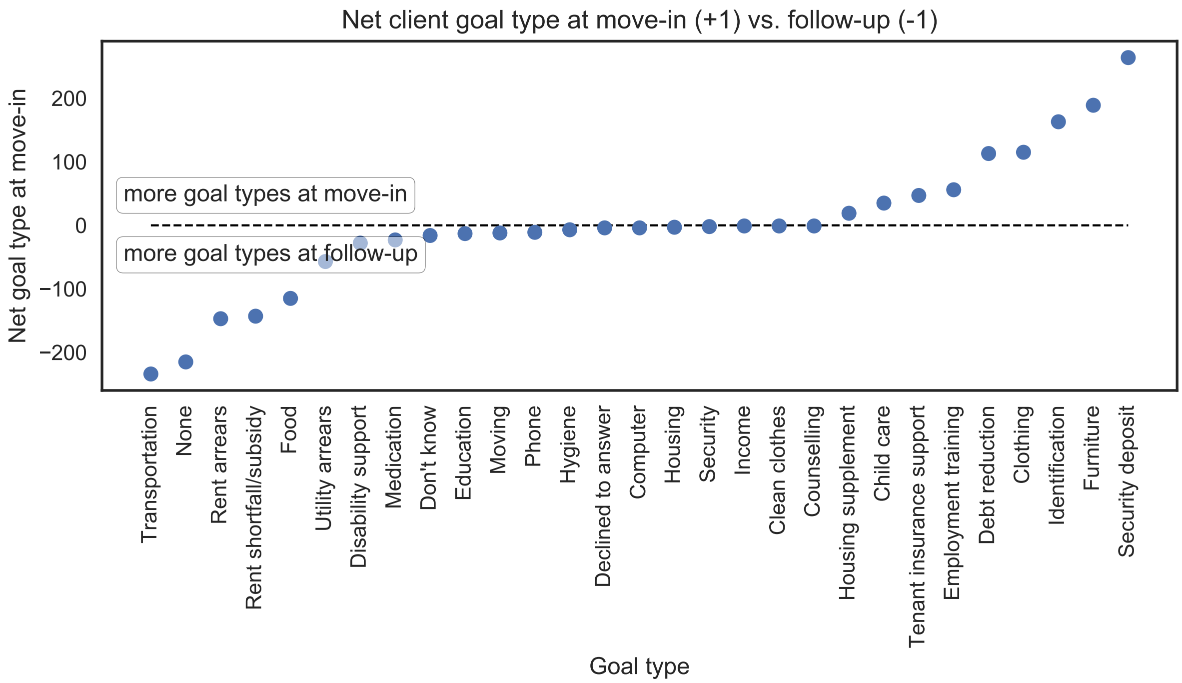

Figure 6.2: Net clients by goal types

In Figure 6.2, the 498 clients that only reported goals at move-in are not included. Of the 1,588 clients that remain, the number of goal types at follow-up is subtracted from the goal types at move-in. For each goal type along the horizontal axis, the vertical axis indicates the net difference between clients that had this goal type at move-in and those that had it at a follow-up. For goal types that were requested more often by clients at move-in than at follow-up, the net count is above 0 on the vertical axis. For goal types that were requested more often at follow-up than at move-in, the net count is below 0 on the vertical axis. As can be seen, nine goal types were reported more often at move-in than at follow-up, including "security deposit," "furniture," and "identification." These goal types can be interpreted as important requests at the time the client moves into their new home. Other goal types were reported more frequently during follow-up interviews, including "transportation," "rent arrears," "rent shortfall/subsidy," and "food." These goal types can be interpreted as requests that are required after the client has successfully moved in. Several goal types were requested at follow-up with similar frequency compared to move-in, including "moving" expenses, "phone," "hygiene," and requesting access to a "computer." These goal types represent requests equally important at the beginning and continuously throughout the program.

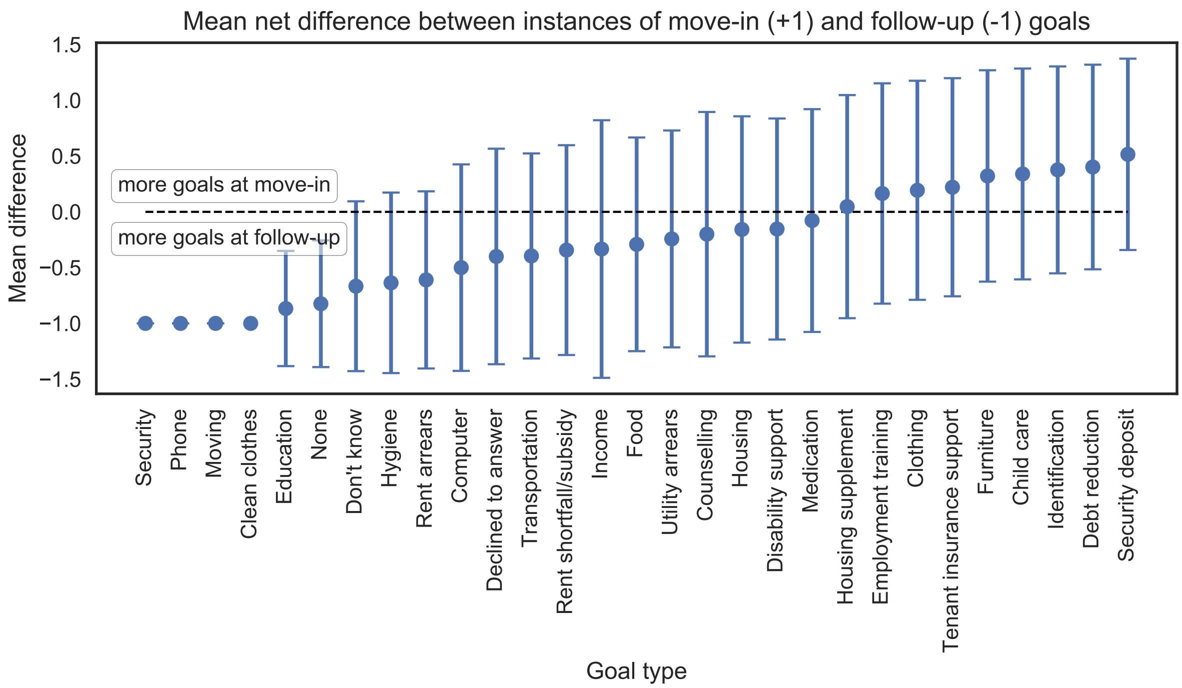

Figure 6.3: Mean net difference by goal types

Finally, Figure 6.3 is similar to Figure 6.2 but rather than taking the net difference between counts of clients per goal type, the graph in Figure 6.3 takes the mean net difference between goal types for a client at move-in and follow-up. This graph is also limited to the 1,588 clients that had follow-up goals. Here, we see similar goal types above as in Figure 6.2. However, Figure 6.3 shows the degree to which each goal type differs between move-in only and follow-up only. Rather than summing the differences, the mean value for each client is taken between move-in (+1) and follow-up (-1), along with the standard deviation. Here we see that despite the nine goal types above zero, indicating more goals types at move-in, the standard deviation of the values spans across the zero threshold. This shows that, in the case of mean > 0, even though the on average majority of clients requested more of these goal types at move-in over follow-up, some clients requested those goal types at follow-up only. Also, on the left hand side, we see that some goal types were only requested at follow-up as their standard deviation is zero and mean value is -1. These are “security,” “phone,” “moving,” and “clean clothes” goal types. The goal types with mean close to zero indicate that these goals had many clients with the same number of goals at move-in and follow-up. However, the standard deviation indicates some were found with more goal types in one form than the other.

6.1.4 Demographics Distribution

The initial objective for evaluating the CHF-HF dataset was to predict client outcomes based on similar evaluation of the At Home/Chez Soi (AH-CS) project [257]. Volk et al. performed predictive analysis to determine whether client characteristics at intake can be used to predict successful exit from the program. A full description of the program can be found at [95]. The initial predictive analysis on the CHF-HF dataset produced similar results. These results are presented in Appendix E.1. Both studies, AH-CS and CHF-HF, produced weak models with prediction accuracy improvements of only 3.8% and 4.8%, respectively, over random selection.

The weak prediction confirmed the hypothesis that predicting client outcomes based on demographics at intake is insufficient, and may require a deeper understanding of client interaction with the program. Relying on the ANOVA method, analysis presented in Appendix A.3 reveals key client characteristics with $p \geq 0.05$ that should be used to make predictions about outcomes in the CHF-HF program. Table 6.1 lists these key characteristics as well as easily obtainable characteristics like age and gender.

Table 6.1: Key demographic attributes of CHF participants

Attribute	**Description**
GAge	Age range.
Gender	Client's gender.
CIC	Citizenship status.
PrimRes	The client's primary residence before joining the program.
AbsRel	Whether client is absolutely or episodically homeless.
Employed	Client's employment status.
UempDur	Duration of unemployment.
EmpAbility	Whether the client is able to hold employment.
InstitutionalizedDays	Number of days spent institutionalized.
MentalIssue	Whether the client experiences mental health issues.
MentalFacil	Whether the client spent time in a mental health facility in the past 12 months.
PhysProb	Whether the client lives with any physical health issues.
HealthFacil	Whether the client came into the program from a health facility.
Addict	Whether the client suffers from addiction, treated or otherwise.
FamilySitu	Family status.
Sector	Family sector.
Basic Need	Basic needs requested by client.

GAge captures the client's age bracket (<18, 18-24, 25-35, 36-50, 51-64, and >65). **Gender** captures the client's gender as either male, female, or transgender. **CIC** identifies the client as a Canadian citizen, a refugee, or other status. The client's family situation is captures by the **FamilySitu** attribute, and includes "single," "single parent family," "a couple," "head of household," or "unknown." A related attribute is **Sector**, which identifies the service sector the client is best suited for based on their **FamilySitu** attribute. **PrimRes** captures the client's primary residence before joining the program. This field captured a variety of values including: sleeping rough (outside), in short-term subsidized rental housing, in long-term rental housing, with family (couch surfing), with child intervention services, an addiction facility, or another institutional facility. **AbsRes** identifies the client as absolutely homeless or relatively homeless. **Employed** captures the client's current employment state, whether it is full-time, part-time, or not employed. **UempDur** captures how long the client was unemployed before joining the program, or "unknown." **EmpAbility** identifies the client's ability to be employed or not. **InstitutionalizedDays** captures the number of days a client was institutionalized, whether in a hospital, prison, or other facility. **MentalIssue** captures whether the client is experiencing any mental health issues with responses yes, no, or don't know. A "yes" response captures treated, untreated, and partly treated and untreated. **MentalFacil** is true if the person spent time in a mental health facility in the past 12 months. **PhysProb** is a yes/no attribute indicating whether the client lives with a physical disability or not. **HealthFacil** captures whether the client stayed in a healthcare facility immediately before being referred to the intervention program, or if this is unknown. **Addict** is a yes/no attribute identifying the client as currently being addicted to any drugs or alcohol, whether in recovery or not. Finally, the HF Assessment form used by the CHF-HF program provides 21 "basic needs" a client can select, plus an open field for "other." Based on the values collected, there were 763 different basic needs requested by CHF-HF participants at program intake and at three-month follow-up interviews. Some participants have gaps between follow-up interviews when they went "missing." The 763 different values provided were combined into 58 different need categories.

6.1.5 Motivating Scenarios

The captured data can be used in a number of ways. For example, the AH-CS study [257] described in Section 6.1.4 used evaluates a program by identifying the percentage of clients who were successful in the program. The criteria for eligibility for a program is the probability a participant will be successful based on their information at intake. With a Housing First program it is not clear which cohorts are successful [257]. Since simply relying on demographics is not sufficient, the motivating scenarios arise from understanding the interaction between clients and the program. The following two motivating scenarios for an ontology are introduced.

How to monitor client progress?

For program administrators, whether a primary investigator in a study or a case manager at a shelter, monitoring client progress is often difficult, especially for programs like Housing First. In a "treatment-as-usual" program, a client's treatment compliance is closely monitored as it is considered the first step necessary towards recovery [247]. The Housing First program, however, encourages client choice, allowing the client to use services in the order they request them in. It is therefore important for the program administrator to understand what a client needs, when, and how best to make services and required resources available to them. This is not an easy task, as client needs change greatly over time [257]. Without conducting an in-depth interview about preferences, the order client requests are made in serves as a proxy for the client's preferred order. Reviewing information about clients at intake is not sufficient for understanding how their needs will progress while participating in a Housing First program. A better understanding of how clients use the services is required, including when their needs change and how best to align programs with changing needs.

How to monitor service delivery performance?

By placing less emphasis on treatment compliance, the service provider is exposed to many unknown factors. Such uncertainty may impact the quality of services they provide. It may become harder to schedule resources in anticipation of a client's changing needs. A major factor is the client's susceptibility to influences outside of the control of service providers. Service providers must identify which cohorts of clients are impacted by such influences and make efforts towards understanding those influences. With this level of knowledge about clients and their needs, a provider can better anticipate changes in client needs and proactively assist clients on their next phase of a client-guided program like Housing First.

6.1.6 Competency Questions

Competency questions derived from motivating scenarios are meant to evaluate the proposed ontology. The first group of questions (Q-1 to Q-16) examines the ontology's ability to represent data provided in the CHF-HF dataset. Focus is placed on the requests made by clients. This includes mapping the requests to Maslow's hierarchy, capturing the order of requests, and associating them with possible motivations and constraints that prompted the requests. The order in which goals are requested in the data represents the client's preferred order. Maslow's order is captured by an MH ranking. The practical order (the order in which goals were satisfied by specific services) is not included in the dataset but can be captured by OSSN if an execution trace log was provided. Such a trace log defining the practical order can also be provided by a simulation, which begins with the client's preferred order but finishes with the order services were delivered in. This approach is discussed further in Chapter 7. The competency questions can then ask whether a service provider (practical ranking) matched the client's preference (agent ranking). OSSN also captures client demographics which are provided in the CHF-HF dataset. Using the provided demographics, OSSN infers the correct MH level to map participant requests to. The competency questions can then ask whether a client's preference (agent's ranking) matched Maslow's hierarchy (MH ranking), given their demographics.

The second group of questions (Q-20 to Q-29) evaluates the ontology's ability to capture services available to the clients. By associating services with client constraints, the objective is to answer questions about service provisioning from the perspective of the client.

The third group of questions (Q-30 to Q-37) examines the ontology's ability address the dynamic aspects of requests made and how that impacts goal reranking. Questions touch on the plan generation and execution phases of the client's decision making.

Competency Questions: Group 1

Client questions address the three main concepts captured about clients: their needs, constraints, and demographics.

Q-1 What goals does client X have?

Q-2 How does client X rank their goals?

Q-3 Based on requests made, what MH-level needs is client X requesting?

Q-4 Is the practical order of goals for client X the same as MH?

Q-5 What needs are requested by clients in demographic X?

Q-6 Which clients request needs at MH level X?

Q-7 Which demographic is asking for MH need X most?

Q-8 What do clients with demographic X need most?

Q-9 Does client X ask for goals in the same order as client Y?

Q-10 What motivates clients with demographic X?

Q-11 What constraints are faced by clients with demographic X?

Q-12 What percentage of clients are constrained by lack of courage?

Q-14 What percentage of relatively homeless clients that are requesting furniture are not elderly?

Q-15 What can motivate clients to use service X?

Q-16 Are wrong conditional goals assigned to any client, based on their demographic and MH level?

Competency Questions: Group 2

The second group of questions examines the ontology's ability to represent whether services help with satisfying client needs.

Q-20 What client attributes are correlated with their progress in a program?

Q-21 Which types of services are aligned with which client goals?

Q-22 What services can be categorized as "family services?"

Q-23 What services are needed together to address "child care goals"?

Q-24 What resources are needed to address a client's "child care goals"?

Q-25 What resources and servicea are needed to address a client's security-level needs?

Q-26 How well do programs address physiological and security needs of clients?

Q-27 Are resources available when needed?

Q-28 How did other pilot projects perform in satisfying client needs with comparable services that deliver the same resources?

Q-29 When should a program intervene in a client's progress?

Competency Questions: Group 3

The third group of questions evaluates OSSN's ability to answer questions about the client's decision making during the plan execution phase.

Q-30 What interim goals are required to satisfy goal X?

Q-31 What clients are and are not observed to follow a planned order?

Q-32 What percentage of clients execute emotional plan?

Q-33 What percentage of emotional plans have goals at MH level X?

Q-34 Which client demographic makes repeat requests?

Q-35 Which client demographic makes repeat MH-level requests?

Q-36 When is the best time to schedule visits with client X?

Q-37 When is the best time to schedule follow-up visits with client X?

6.1.7 Related Ontologies

The ontologies introduced in Section 2.5.5 overlap with the proposed ontology, and do address some of the competency questions. These, however, are service-oriented, focusing on modelling processes and constraints of the service provider rather than impact on client outcomes. Each ontology represents the client as an actor that interacts with the provider. The Open Eligibility Project (OEP) is a taxonomy of services offered to clients [11]. The services are categorized as "emergency," "food," "housing," "goods," "transit," "health," "money," "care," "education," "work," and "legal." Each category provides a taxonomy of subcategories (is-a relations) of specific services. The client is represented by the "human situations" category. It includes age group, citizenship status, criminal history, disabilities, health, household, and urgency. The objective of OEP is strictly to create an open and sharable vocabulary of services. No definition is assigned to each term, hence they are open to interpretation. For example, there is no formal definition of what constitutes an emergency other than being assigned the label of "In Crisis," "In Danger," or "Emergency." The services are not connected by semantic or functional relations, making any definitions of process or constraints across implementations informal.

The Global City Indicator (GCI) ontology focuses on housing, and classifies clients as absolutely or relatively homeless [259]. The resources available to the clients are different types of housing. The competency questions GCI addresses deal with details about specific households and aggregate information about city resources. For example, data collected using GCI can answer who the individuals in a particular household are, and whether that household is considered a "slum household." Also, it captures information required to identify which living conditions, as outlined in UN-HABITAT, a household is lacking. GCI also captures aggregate information about households in a city. These include average housing size, number of slums per household, and the total slum population of a city.

The INSPIRE ontology captures the processes and resources of the service provider, focusing on elderly and adults living with disabilities [195]. A client's needs can be categorized as physical or social needs, or a combination of the two, along with an urgency indicator. This is used to efficiently identify the appropriate department to transfer a client to. For example, social services include "care facilities," "career guidance," and "foster care." Services specifically for the elderly may include "home care" for totally or partially dependent and "basic care" for dependent, disabled, and alone elderly. Any "complex" cases are sent to the Centre of Complex Cases (CCC), where a case manager is assigned based on their competency and the client's needs. Based on the assessment, clients are assigned resources available through the service provider. While the available services and internal workflow are well represented, the information required to captured the client's needs, urgency for need, and underlying symptoms are not captured by the INSPIRE vocabulary. The competency questions INSPIRE can answer are ones that deal with service assignment. For example, given a client's age, disability, and severity, they are assigned a specific service, or passed to the CCC. The execution of steps required for service assignment and application are then monitored. Service monitoring includes reevaluation of service provisioning.

6.2 CHF-HF to Maslow Mapping

To begin the process of mapping CHF data to BRAMA, this section provides the definitions used to create the mapping *MH* that maps basic needs identified by the CHF-HF dataset to Maslow's hierarchy [160]. In order to capture homeless client needs more accurately, the original definitions for Maslow's levels must be modified. The four key modifications to the original hierarchy are presented in the next section. The final definitions are provided in Table 6.2 on page 129.

6.2.1 Maslow's Hierarchy For Homeless Clients

Maslow's original terms were defined for the general population. Lower-level goals, like having food or being safe from existential threats, can be applied universally across an entire population. Higher-level needs are more abstract. Any mappings to explicit goals must be mapped carefully to capture the intended purpose of the goal. For example, Maslow included "independence" as a basic esteem need [160], which can be mapped to several goals. For example, moving out of a boarding house into an apartment could be mapped to "esteem" as per Maslow's original mapping. However, it can also be mapped to "security" as boarding houses are often unsafe. Similarly, returning to school to get a better job can be mapped to "esteem" as it falls under Maslow's intended roles like mastery, prestige, and status. It also indicates the need for self improvement, realizing personal potential, and personal growth. Such needs are better represented as self-actualization. The next four sections describe similar changes that need to be made to Maslow's original order to correctly capture the needs of homeless clients. While the ontology lacks a temporal dimension, changes in a client's demographics will change the level to which the same request is mapped. For example, as a client ages, their need for a phone changes from a social need to a security need.

Shelter is not always a biological need

Sumerlin pointed out that even though lack of shelter is a defining characteristic of homeless people, the lack of food (physiological need) is the greatest threat to a homeless person's survival [240]. However, the idea of "having shelter" can be mapped to a physiological need as it protects against environmental factors like extreme cold weather. This is an example of conditional goal mapping. Whether the agent is absolutely or relatively homeless determines the MH level to which a request for shelter is mapped. The justification for this conditional mapping is that someone who is sleeping on the street is exposed to harsh environmental factors that have a physical impact on their health. This distinction is highlighted by the related HF Assessment question:

> *Are you absolutely (i.e. emergency shelter or street) or relatively (i.e. living in spaces that don't meet the health and safety standards) homeless?*

Hence, shelter is only a physiological need for the "absolutely" homeless, and a security need otherwise.

Shelter as a security need

The definition of security needs for people experiencing homelessness aligns better with Maslow's examples of the security level. For this population, this definition includes lack of protection from "aggression and victimization" risks [240], and excludes environmental factors. Having shelter significantly increases a "relatively" homeless person's protection from such risks, offering a sense of security. For example, sleeping at night exposes homeless people to various safety risks and many choose to stay awake at night and sleep during the day. At the same time, managing to have a restful sleep during the day is difficult in "crowded, noisy, and dirty streets," causing further nighttime victimization in part due to sleep fatigue [176]. Hence, shelter for relatively homeless clients is categorized alongside security needs as it provides this sub-population with protection from security issues that include aggression and victimization [240].

Self-actualization is a motivating factor across all levels

Self-actualization in homeless people is not a need activated once all other needs are met, as implied by Maslow's original hierarchy [160]. Rather, it is an iterative process of self-improvement that propels people towards achieving their needs, as described by Henwood et al. [111]. A self-actualized person has the "courage, openness to experience, and attainment of high personality growth." A non-self-actualized person is "fearful, rigid, and unfulfilled." Henwood et al. observed that self-actualization is exhibited differently by housing-first (HF) and treatment-first (TF) participants [111]. HF participants are given the freedom to make requests and ask for help about goals mapped to any MH level, without worrying about the hierarchical order. TF participants, when faced with constraints imposed by the service provider, became self-actualizers "when more basic needs were not met." Here, needs for self-actualization "emerge from the frustration, not fulfillment, of basic needs." For TF participants, finding a permanent home "facilitated a step-wise approach to thinking through subsequent goals to improve one's life" in a non-hierarchical fashion. In both the HF and TF scenarios, self-actualization motivates clients to continue seeking and achieving goals that satisfy unmet needs across all levels of Maslow's hierarchy.

To differentiate between a "*need*" at a particular level and a "*self-actualizing motivation*" towards unmet needs across multiple levels, the mapping relies on Sumerlin's interpretation for self-actualization in the homeless context. Sumerlin states that "self-actualization represents a global aspect of personality indicative of optimal function" [240]. For a homeless person to exhibit a global optimal function they require "unconditional self-acceptance" and "adaptive striving." This can be achieved by exhibiting in-depth reasoning and long-term commitments to a need. Considering again the participants described by Henwood, their needs required the creation of more complex plans with complex means to satisfy unmet needs. Following Sumerlin's explanation, self-actualization motivated participants to rely on optimal function to create such a plan. They were able to employ in-depth reasoning and make long-term commitments.

This type of reasoning and commitment can now be used to categorize each need simply as an "*unmet need*" or a "*self-actualizing motivation*" towards unmet needs. We characterize "*unmet needs*" as "short-term goals" that can be achieved using known means without an elaborate plan. For example, requesting more opportunities to participate in social activities is a short-term goal that satisfies the social MH need of being more social. In contrast, "*self-actualizing motivation*" is characterized by a "long-term goal" towards achieving a long-term need. For example, requesting a mentor is a long-term goal towards bettering oneself. A social worker can then provide information about a suitable mentor that will help the client better themselves over several sessions. Given these examples, a person looking for "socializing opportunities" will be categorized as seeking an unmet social need, while a person looking for a "mentor" will be categorized as seeking a self-actualization need. If a homeless person is looking for both, they can be categorized as seeking a social need and a self-actualization need.

Family needs are not necessarily social needs

Traditionally, the need to be close to family is a social need. However, for heads of households that provide for their immediate and extended family, needs of dependents are categorized as personal needs. Such needs fall under one of the other levels. For example, consider an agent that requests help obtaining baby formula for its infant child. In OSSN such a request is mapped to the physiological level as if food was requested for the agent. In general, the requests made on behalf of individuals under the agent's care are mapped to the MH level associated with the request, not the agent's motivation for social needs.

Table 6.2: Maslow's hierarchy of needs [160]: **modified according to* [176, 240]

Need	**Definition**	**Example* [160, 176, 240]**
Biological and Physiological	All biological requirements are combined, with the exception of "shelter" which is only included for the absolutely homeless [176, 240].	Air, food, drink, sex, sleep, shelter (absolutely homeless).
Security needs	Any causes of "aggression and victimization," including those caused by lack of shelter for relatively homeless [176, 240]	Protection from elements, security, shelter (relatively homeless), order, law, stability, freedom from fear.
Social: Love and belongingness needs	A homeless person's social network may play a nonstandard role in their life compared to non-homeless people. The role can be situational. "A homeless person's network is smaller and less satisfying than those of domiciled people; hence, a homeless person suffers deficiencies of love and belonging" despite being in social situations surrounded by their peers [240].	Friendship, intimacy, trust and acceptance, receiving and giving affection and love. Affiliating, being part of a group (family members a person is not providing for, friends, work, desire to have children).
Esteem needs	Esteem needs are achieved by homeless people when they either *overcome* or *accept* their circumstances [240]. Acceptance may occur "when a personal identity as a homeless person is embraced."	Achievement, mastery, independence, status, dominance, prestige, self-respect, respect from others.
Self-Actualization needs	Autonomy, movement toward capacity, courage, curiosity, democratic character, (lack of) fear of one's own greatness, openness to experience, purpose in life, self-acceptance, comfort with solitude, and an ability to integrate the past, present, and future [240].	Realizing personal potential, self-fulfillment, seeking personal growth and peak experiences.

6.3 Ontology of Social Service Needs

Based on the changes to Maslow's hierarchy in Table 6.2 and mappings between client needs and HF Assessment data, we can extend basic semantics between goals and MH needs from Section 3.4.1. The extension is specific to the social service domain based on data captured by the HF Assessment forms and the complete mappings in Appendix B. The proposed extension, OSSN, captures semantics between an agent interacting with social services. OSSN must capture the agent's expressed goals, motivations for those goals, MH level, goal preferences, and what is constraining the agent from achieving its goals. OSSN must also capture the semantics between constraints and services the agent interacts with. These key OSSN concepts are summarized in Table 6.3, while their relations are illustrated in Figure 6.4.

6.3.1 Need Semantics

Each need has a set of semantic relations that associate an agent's need to the service that satisfies it, as per Table 6.3. An agent's relations include its Maslow **needs**, **preferred order** ranking, followed by a concrete **goal** requested by a participant, personal **motivation** for that goal, and **constraints** preventing goals from being satisfied. The agent's need is mapped to an MH level, as per Table 6.2. A mapping to an MH level is meant to ground the concrete goal proposition $s_i \in G\text{-}BR$ provided by participants on the HF Assessment questionnaire. It also provides the preference relation between goals. The order in which goals are provided on the HF Assessment form is assumed to be the preferred order, where goals given earlier are assumed to be preferred by the agent. Whether it is a true preference ($rank(A, s_i)$) or simply a learned practical order from $rank(x, s_i)$ from some previously executed plan P^x, is not known. **Motivation** is a description of why an agent might want to pursue this goal. It provides additional information for mapping a particular goal to the appropriate MH level. For example, "child care" is a broad category of needs associated with the agent's child's needs. The motivation to keep a child out of harm's way would associate a goal with the physiological level, as it prevents physical harm. This may include a request for emergency child care and contacting child protective services. Child care may also be motivated by wanting to raise well-adjusted and social children. For example, a child care goal to provide toys and arrange activities with their peers aims to increase an agent's child's self esteem. Such goals would then be mapped to the agent's esteem level.

The service provider is represented with resources and services that relieve an agent's constraints. The **constraint** that prevents an agent from achieving its goals is relieved by providing a useful **resource**. For example, the constraint preventing an agent from providing toys or social activities for its children might be a lack of money or not knowing about available activities (i.e. lack of information). Resources may include any donated presents at a shelter or a holiday donation drive. Resources may also include advocating for a child and helping them sign up at a youth program administered by a shelter, or providing information on where such services are available. Finally, the **service** represents the service provider, program, or department that makes the resource available to the agent. For example, family services would provide children with toys or access to youth programs. In cases of emergency, child protective services would provide a social worker or a counsellor.

Table 6.3: Basic properties of *client* needs and their relation to a service *provider* captured by the CHF-HF dataset

Owner	Property	HF Assessment Field	Description/Example
Client	Need	Mapped to an MH Goal.	A basic need in Maslow's hierarchy with justification. For example, "physiological" or "security" as per definition in Table 6.2.
Client	MH Goal	A Goal mapped directly to an MH Need.	For example, "not being hungry" is goal directly linked to the "physiological" MH Need.
Client	$rank(A, s_i)$	Order of *Needs* provided in the initial and follow-up HF Assessment questionnaires is assumed to be the agent's preferred order.	Preferred order of needs dictates how clients rank them, where earlier needs are more important than later needs at specific periods.
Client	Motivation Description	Reasons for needs expressed by client.	The description allows a practitioner to classify a need into the appropriate MH level. This was not supplied by the data, but would be provided by a client.
Client	Goal	*Basic needs assistance*, *Health information*	For example, obtaining "special formula for infant" or a "birth certificate."
Client / Provider	Constraint	Context-specific, including missing information, inadequate funds, or insufficient training.	A constraint is anything that prevents a client from achieving their goals. A constraint can be a functional prerequisite or a goal prerequisite.
Provider	Resource	*Service referral*, *Case worker contact*, *Income*, *Employment training and education*	A resource that is meant to be used by a client to satisfy a constraint.
Provider	Service	*Service referrals*, *Case worker contact*	Makes specific resources available to a client, such as "daycare" or "detox program."

6.3.2 OSSN: Formal Definitions

This section provides the formal definitions for OSSN, represented in OWL syntax [140, 115]. OWL (Web Ontology Language) was chosen since it is one of the most common ontology languages on the Semantic Web [113]. In Section 6.3.3, several goal mapping examples are provided to demonstrate how to represent agent goals using OSSN. All classes and properties are provided in Appendix B. Main OSSN classes and properties are represented in Figure 6.4. Key OWL classes are also provided as individual OWL axioms.

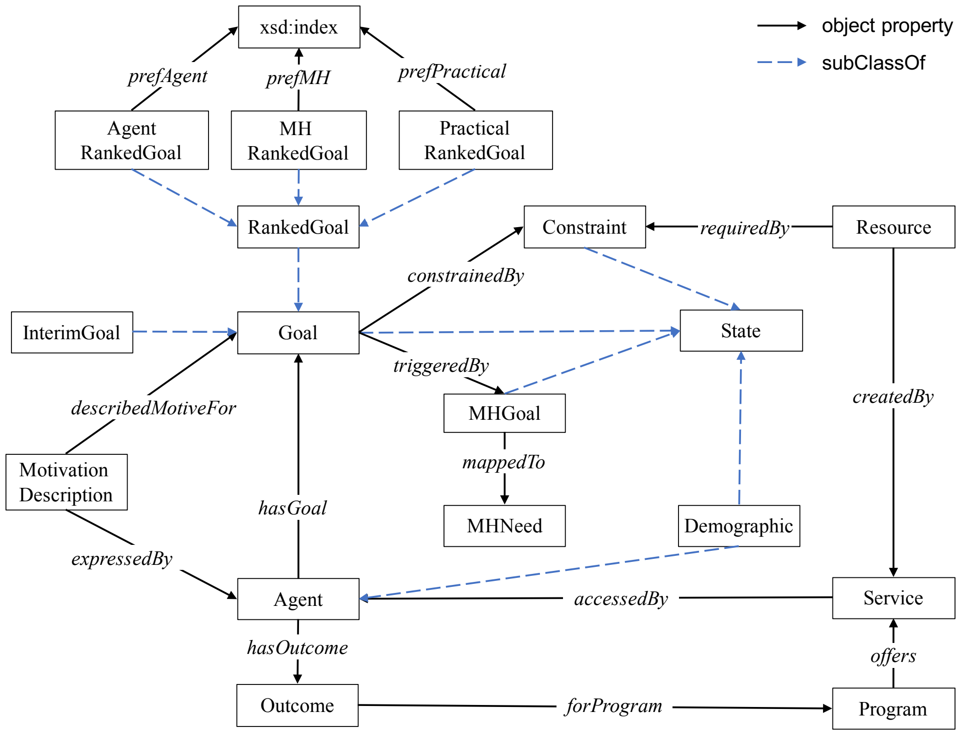

Figure 6.4: Ontology of Social Service Needs relation diagram

Agents and Goals

A BRAMA agent is goal-driven, hence the basic property that defines an agent is having a goal. In axiom O-1 the property *hasGoal* defines the *Agent* class as one that has at least one *Goal* state $s_i \in G\text{-}BR$. Axiom O-2 defines the *Goal* class as a state that is triggered by some underlying MH need but constrained from being true.

OWL 1 (Agent Class).

$$Agent \sqsubseteq \exists hasGoal.Goal \tag{O-1}$$

OWL 2 (Goal Class).

$$Goal \sqsubseteq State \sqcap \exists triggeredBy.MHGoal \sqcap \exists constrainedBy.Constraint \tag{O-2}$$

The motivation for goals is expressed by agents to indicate the reason for requesting the goal. The $MotivationDescription$ class captures this description and provides additional context for the request.

OWL 3 (MotivationDescription Class).

$$MotivationDescription \sqsubseteq \exists describedMotiveFor.Goal \sqcap \exists expressedBy.Agent \tag{O-3}$$

Ranked Goals

A goal state can be preferred over another, as defined by the ordering relation $\succ_x$. If a preference is assigned to a goal it is considered a subclass of the *RankedGoal* class, with a unique ordering relation. A *RankedGoal* is any goal that has an integer preference assigned to it with the *pref* data property, as defined by axiom O-4. The *pref* data property has three sub-properties, *prefPractical*, *prefMH*, and *prefAgent*.

OWL 4 (RankedGoal Class).

$$RankedGoal \sqsubseteq Goal \sqcap \exists pref : xsd{:}integer \tag{O-4}$$

The ordering relation $\succ_{MH}$, as defined in Section 3.4.2, is set by Maslow's hierarchy and represented in OSSN by the property *prefMH*. A goal ranked by MH is an *MHRankedGoal* class as defined in axiom O-5. It is a subclass of the intersection between a *RankedGoal* and a class with *prefMH* relation to an integer value. For example, the goal *Food* is an *MHGoal* mapped to the physiological *MHNeed*. The assertion *prefMH*$(Food, 1)$ would specify that the physiological level *Food* is mapped to is the most important level.

OWL 5 (MH RankedGoal Class).

$$MHRankedGoal \sqsubseteq RankedGoal \sqcap \exists prefMH : xsd{:}integer \tag{O-5}$$

For each MH level, a *Goal* subclass is defined that relates that goal to its MH level, as per axioms O-6.a to e. Such a *Goal* subclass is deduced from the goal being assigned an MH level explicitly with *prefMH* or by being triggered by an *MHGoal* assigned to an MH level. For each MH level, a specific ranking class that relates *prefMH* to the type of *MHGoal* it is triggered by:

OWL 6 (MH Level RankedGoal Class).

$$GoalPhysiological \sqsupseteq prefMH{:}1 \sqcup \exists triggeredBy.MHGoalPhysiological \tag{O-6.a}$$

$$GoalSecurity \sqsupseteq prefMH{:}2 \sqcup \exists triggeredBy.MHGoalSecurity \tag{O-6.b}$$

$$GoalSocial \sqsupseteq prefMH{:}3 \sqcup \exists triggeredBy.MHGoalSocial \tag{O-6.c}$$

$$GoalEsteem \sqsupseteq prefMH{:}4 \sqcup \exists triggeredBy.MHGoalEsteem \tag{O-6.d}$$

$$GoalSelfActualization \sqsupseteq\ \equiv prefMH : 5 \sqcup \exists triggeredBy.MHGoalSelfActualization \tag{O-6.e}$$

The ordering relation $\succ_A$, as defined in Section 5.5, is set by an agent. It is represented in OSSN by the *AgentRankedGoal* class as defined in axiom O-7. It is a subclass of the intersection between a *RankedGoal*, and a class with both *prefAgent* and *hasGoal* relations. For example, given *Goal* states $s_i, s_j \in$ *G-BR* along with the assertions *hasGoal*(A, s_i), *hasGoal*(A, s_j), *prefAgent*$(s_i, 1)$, and *prefAgent*$(s_j, 2)$, the goal state s_i is preferred by agent A over s_j.

OWL 7 (Agent RankedGoal Class).

$$AgentRankedGoal \sqsubseteq RankedGoal \sqcap \exists rankedBy.Agent \sqcap \exists prefAgent : xsd{:}integer \tag{O-7}$$

Finally, the practical ranking of goals represents the order in which goals were satisfied during plan execution. This order is observed in the outcome of a plan following its execution. The data property *prefPractical* captures this relation, as defined in axiom O-8. The practical rank is captured by logging a trace of an executed plan. For example, the goals s_i and s_j ranked by agent A above can be satisfied in reverse order. The assertions *prefPractical*$(s_i, 2)$ and *prefPractical*$(s_j, 1)$ capture this order.

OWL 8 (Practical RankedGoal Class).

$$PracticalRankedGoal \sqsubseteq RankedGoal \sqcap \exists prefPractical : xsd{:}integer \tag{O-8}$$

Goal Constraint

A goal state is constrained by the *Constraint* class, a state $s_j \in S\text{-}BR$ that prevents the goal state from being true. Hence, a constraint is a high-level summary of unsatisfied preconditions preventing a client from achieving their goals. For example, an agent cannot buy food from a store if it does not have money. Having money is a precondition state that must be true before purchasing food. The state $not(A, money) \in S\text{-}BR$ is a *Constraint* that prevents the *Goal* class $not(A, hungry)$ in $G\text{-}BR$ from becoming true. For a state to be a constraint, it must also be resolvable by a resource. A non-resolvable constraint identifies an incorrect goal or action. For example, requesting legal advocacy from a housing worker describes an incorrect action if the goal is to find housing. Conversely, if the goal is to resolve legal issues than the action is correct, but the outcome is not. In either case, there is a mismatch between the action and goal.

In the more general case, the agent is attempting to resolve a constraint without a service that provides the required resource. Hence a *Constraint* class is a *State* class that requires a *Resource* class ($requiredBy^{-}.Resource$) and is actively constraining a *Goal* class ($constrainedBy^{-}.Goal$), as defined in axiom O-9.

OWL 9 (Constraint Class).

$$Constraint \sqsubseteq State \sqcap \exists requiredBy^{-}.Resource \sqcap constrainedBy^{-}.Goal \tag{O-9}$$

MH Goals and Interim Goals

As stated previously, the *Goal* class represents requests made by an agent. Requests for basic goals are triggered by an underlying MH level need associated with it. *MHGoal* represents such a need that triggers the requested goal. Each *MHGoal* is mapped to one or more MH levels. For example, while $moneyForFood$ is a *Goal*, $notBeHungry$ is the *MHGoal* state that triggers it. $notBeHungry$ is then mapped to the physiological MH level. In OSSN, the *triggeredBy* property captures the relation between a requested *Goal* and its underlying *MHGoal*. The $mappedTo$ property captures the relation between the *MHGoal* and its underlying MH level class $MHNeed$. These classes are defined in axioms O-10 and O-11.

OWL 10 (MHGoal Class).

$$MHGoal \sqsubseteq \exists triggers.Goal \sqcap \exists mappedTo.MHNeed \tag{O-10}$$

OWL 11 (MHNeed Class).

$$\begin{aligned} MHNeed \equiv & \exists mappedTo^{-}.MHGoal \sqcap \\ & \{physiological \sqcup security \sqcup social \sqcup esteem \sqcup selfActualization\} \end{aligned} \tag{O-11}$$

We also define an *MHGoal* mapped to each type of $MHNeed$, as defined in axioms O-12.a to e.

OWL 12 (MHGoal Level Classes).

$$MHGoalPhysiological \sqsubseteq MHGoal \sqcap mappedTo{:}physiological \tag{O-12.a}$$

$$MHGoalSecurity \sqsubseteq MHGoal \sqcap mappedTo{:}security \tag{O-12.b}$$

$$MHGoalSocial \sqsubseteq MHGoal \sqcap mappedTo{:}social \tag{O-12.c}$$

$$MHGoalEsteem \sqsubseteq MHGoal \sqcap mappedTo{:}esteem \tag{O-12.d}$$

$$MHGoalSelfActualization \sqsubseteq MHGoal \sqcap mappedTo{:}selfActualization \tag{O-12.e}$$

The *Goal* class also has a subclass for interim goals, subgoals that are required to satisfy goal preconditions, as defined in Section 4.3.3, rather being mapped to an *MHGoal*. For example, wanting food is a physiological goal while walking to the store in order to buy food is an interim goal. The *InterimGoal* class is defined as a subclass of *Goal* that is not mapped directly to an MH level, as defined by axiom O-13.

OWL 13 (InterimGoal Class)**.**

$$InterimGoal \sqsubseteq Goal \sqcap \neg\forall mappedTo.MHNeed \tag{O-13}$$

Conditional Goal And Agent Demographics

A conditional goal is a type of *MHGoal* conditional on an agent's *Demographic* class. For example, the goal for temporary housing for absolutely homeless agents is mapped to the physiological MH level. For agents that are relatively homeless it is mapped to the security MH level. A *Demographic* is a subclass of *State* class that defines the state of an agent, as per axiom O-14. Special properties define the actual demographic state the agent is in to define the MH level its goals are mapped to.

OWL 14 (Demographic Class)**.**

$$Demographic \sqsubseteq State \tag{O-14}$$

Conditional goals are not defined explicitly. Rather, they are inferred from the demographics of the agents that request them. For example, consider an agent who is absolutely homeless and is requesting temporary housing. The following axioms define how to identify an agent as either absolutely or relatively homeless. First, the property *homelessState* in axiom O-15 has a range of "abs" and "rel" to represent an absolutely and relatively homeless status, respectively. Next, axiom O-16 defines the $AbsHomelessState$ class as the intersection of *Demographic* class and a class for which *homelessState* = *abs*. The third axiom O-17 defines the $RelHomelessState$ class as the intersection of *Demographic* class and a class for which *homelessState* = *rel*.

OWL 15 (homelessState Property)**.**

$$\top \sqsubseteq \forall homelessState.\{abs, rel\} \tag{O-15}$$

OWL 16 (AbsHomelessState Class)**.**

$$AbsHomeless \sqsubseteq Demographic \sqcap homelessState : abs \tag{O-16}$$

OWL 17 (RelHomelessState Class)**.**

$$RelHomeless \sqsubseteq Demographic \sqcap homelessState : rel \tag{O-17}$$

Next, to assert that an agent is absolutely homeless, $AbsHomelessAgent$ is the subclass of the intersection between the *Agent* and $AbsHomeless$ classes, as defined in axiom O-18. Any agent A asserted as type $AbsHomelessAgent(A)$ is categorized as an absolutely homeless agent. Since absolutely and relatively homeless types are disjoint sets, having the same agent classified as both produces an inconsistent ontology. Its relatively homeless counterpart is defined in axiom O-19. Definition of conditional goals is discussed in Section 6.3.5.

OWL 18 (AbsHomelessAgent Class).

$$AbsHomelessAgent \sqsubseteq Agent \sqcap AbsHomeless \tag{O-18}$$

OWL 19 (RelHomelessAgent Class).

$$RelHomelessAgent \equiv Agent \sqcap RelHomeless \tag{O-19}$$

Service Provider and Resources

The service provider is represented by the *Service* class. A service is something that can be accessed by an agent and creates resources. For example, a "social worker" is a multi-functional service offered by a shelter. A social worker can provide a variety of resources, such as booking a bed, information about child care, or finding a suitable mentor. It follows then, that the *Resource* class is defined as something a service creates and that is required by a *Constraint* class.

OWL 20 (Service Class).

$$Service \sqsubseteq \exists accessedBy.Agent \sqcap \exists createdBy^{-}.Resource \tag{O-20}$$

OWL 21 (Resource Class).

$$Resource \sqsubseteq \exists createdBy.Service \sqcap \exists requiredBy.Constraint \tag{O-21}$$

Program and Agent Outcome

The last set of core OSSN classes are those that capture an agent's outcome in a specific program. A program offers multiple services. An agent can access a service, but its outcome is evaluated in the context of the program. Hence, a *Program* class is defined as the subclass of classes that offer a *Service* and have an *Outcome*, as per axiom O-22. The *Outcome* class relates an agent to a particular program, as per axiom O-23. An agent's outcome in a program could be one of *success*, $fail$, *missing*, or *active*.

OWL 22 (Program Class).

$$Program \sqsubseteq \exists offers.Service \sqcap \exists forProgram^{-}.Outcome \tag{O-22}$$

OWL 23 (Outcome Class).

$$Outcome \sqsubseteq \exists forProgram.Program \sqcap \exists hasOutcome^{-}.Agent \tag{O-23}$$

6.3.3 Mapping HF Assessment to OSSN

OSSN is based on data collected by the CHF-HF study by the HF Assessment form. All basic needs recorded were combined into 50 basic needs associated with one or more levels of Maslow's hierarchy. A sixth level was added for non-answers that includes "Declined to answer," "Don't know," and "None." The entire mapping between HF Assessment and MH levels is provided in Appendix B. A few basic needs are presented here. Each goal in *G-BR* is associated with one or more MH levels, depending on the type of goal mapping applied. The final mappings are captured in *MH* and associated with the agent as part of the model $\mathbb{M}$. The enumeration of OSSN axioms is not comprehensive. See Appendix D for the complete OSSN in OWL syntax.

Recall in Section 3.4.1 the introduction of five goal relation types, namely: direct mapping, conditional mapping, unconditional mapping, goal prerequisites, and functional prerequisites. The remainder of this section provides examples of each goal type in OSSN and its OWL representation. Section 6.3.4 to 6.3.6 present goal mappings.

6.3.4 Mapping Direct Needs In OSSN

Direct-mapping goals are those directly associated with a single MH level. Consider the following OWL examples of clothing and advocacy needs.

Clothing

A request made for an article of clothing is directly mapped to the security level, as defined by Maslow [160], hence a request for clothing is the expressed **goal** and **MH goal** mapped to the security **MH need**. The agent's **motivation** for clothing is simply to "be clothed." The concrete **goal** requested is to get "help with buying or receiving clothing." The **constraint** faced by an agent is "lack of money." The **resource** where an agent can receive information about obtaining clothing without money is a "charity." Finally, the **service** offered by the charity that provides clothing is a "donation centre."

As a direct mapping, any clothing goals are mapped to the same level. Hence, any *MHGoal* triggered by a *GoalClothing* type is equivalent to a security class, with no other properties required. The equivalence relation is defined in axiom O-24 and its implementation in functional OWL syntax in assertions O-25 and O-26.

OWL 24 (Clothing MH Level)**.**

$$MHGoalClothing \equiv MHGoalSecurity \sqcap \exists triggeredBy^{-}.GoalClothing \tag{O-24}$$

To associate *GoalClothing* with an agent $chf2$, this scenario introduced the following OWL classes:

OWL 25 (Example Clothing Individuals)**.**

\# who?

$$Agent(chf2) \tag{O-25.a}$$

\# what is the goal and its type?

$$GoalClothing(getJacket2) \tag{O-25.b}$$

\# what's constraining them?

$$ConstraintClothing(lackOfClothing2) \tag{O-25.c}$$

\# what service is needed?

$$ServiceDonationCentre(donationCentre2) \tag{O-25.d}$$

The following OWL properties define specific instances of clothing being requested and which donation centre they can be obtained at:

OWL 26 (Clothing Properties)**.**

\# which goals?

$$hasGoal(chf2, getJacket2) \tag{O-26.a}$$

\# why do they want it? the need?

$$triggeredBy(getJacket2, needClothing2) \tag{O-26.b}$$

\# how is the goal ranked by agent?

$$prefAgent(getJacket2, 1) \tag{O-26.c}$$

\# motivation?

$$describedMotiveFor(beClothedForSpring2, getJacket2) \tag{O-26.d}$$

$$expressedBy(beClothedForSpring2, chf2) \tag{O-26.e}$$

\# what's constraining them?

$$constrainedBy(getJacket2, lackOfClothing2) \tag{O-26.f}$$

\# what resource is needed?

$$requiredBy(resourceCharity2, lackOfClothing2) \tag{O-26.g}$$
what services provides the resource?
$$createdBy(resourceCharity2, donationCentre2) \tag{O-26.h}$$
which service was accessed by agent?
$$accessedBy(donationCentre2, chf2) \tag{O-26.i}$$

Advocacy

Some requests look similar and are mapped to the same MH level, but are associated with specialized services and resources. For example, many general requests require assistance in the form of advocacy, one of the pillars of the Housing First program, in addition to innovation and research [98]. In OSSN, a request for advocacy is represented by two types of needs, both mapped to the security **need**, 'legal' and general 'help' advocacy. They cover any help a client needs that impacts their safety and stability. "Advocacy legal" captures requests for help navigating the legal system. The main **MH goal** is to "reduce stress" caused by interacting with the legal system. The **goal** is to "solve legal matters and related issues," including attending court, legal fees, and guidance. The **motivation** is to resolve legal issues. The **constraint** is the "lack of information, courage, and money" to resolve such issues alone. The **resource** is "legal work" offered by a "legal aid" **service**. Similarly to *GoalClothing*, "advocacy legal" has an equivalent relation to the security level, resulting in *MHGoalAdvocacyLegal*, as defined in axiom O-27 and implemented in assertions O-28 and O-29.

OWL 27 (Advocacy Legal MH Level)**.**

$$\mathit{MHGoalAdvocacyLegal} \sqsubseteq \mathit{MHGoalSecurity} \sqcap \exists \mathit{triggeredBy}^{-}.\mathit{GoalAdvocacyLegal} \tag{O-27}$$

OWL 28 (Example Advocacy Legal Individuals)**.**

who?
$$Agent(chf3) \tag{O-28.a}$$
goal type?
$$GoalAdvocacyLegal(getLegalMatterResolved3) \tag{O-28.b}$$
what's constraining them?
$$ConstraintAdvocacyLegal(lackOfInfoCourageMoney3) \tag{O-28.c}$$
what service is needed?
$$ServiceLegalAid(legalAid3) \tag{O-28.d}$$

OWL 29 (Advocacy Legal Properties)**.**

which goal?
$$hasGoal(chf3, getLegalMatterResolved3) \tag{O-29.a}$$
Why do they want it? the need?
$$triggeredBy(getLegalMatterResolved3, needToReduceStress3) \tag{O-29.b}$$
how is it ranked?
$$prefAgent(getLegalMatterResolved3, 3) \tag{O-29.c}$$
motivation?
$$describedMotiveFor(resolveLegalIssues3, getLegalMatterResolved3) \tag{O-29.d}$$
$$expressedBy(resolveLegalIssues3, chf3) \tag{O-29.e}$$
what's constraining them?
$$constrainedBy(getLegalMatterResolved3, lackOfInfoCourageMoney3) \tag{O-29.f}$$

what resource is needed?
$$requiredBy(resourceLegalWorker3, lackOfInfoCourageMoney3) \quad \text{(O-29.g)}$$
what services provides the resource?
$$createdBy(resourceLegalWorker3, legalAid3) \quad \text{(O-29.h)}$$
which service was accessed?
$$accessedBy(legalAid3, chf3) \quad \text{(O-29.i)}$$

"Advocacy help" is a more general advocacy for non-legal matters. The **MH goal** is also to "reduce stress." The **motivation** is to "reduce critical issues" faced by the client that impact their health. The specific **goal** is to "resolve any outstanding issues" faced by the client. These may include rent disputes, family reconciliation, and acting as a proponent for the client's causes. The **constraint** is the client's "lack of conflict resolution skills." The **resource** and **service** provider is a case worker assigned to the client that manages access to other resources. Similarly to clothing and advocacy legal, advocacy help has an equivalent relation to the security level, as defined in axiom O-30 and assertions in O-31 and O-32.

OWL 30 (Advocacy Help MH Level)**.**
$$MHGoalAdvocacyHelp \sqsubseteq MHGoalSecurity \sqcap \exists triggeredBy^{-}.GoalAdvocacyHelp \quad \text{(O-30)}$$

OWL 31 (Example Advocacy Individuals)**.**

goal type?
$$GoalAdvocacyHelp(getHelpResolvingCriticalIssues3) \quad \text{(O-31.a)}$$
what's constraining them?
$$ConstraintAdvocacyHelp(lackOfConflictResSkills3) \quad \text{(O-31.b)}$$
what service is needed?
$$ServiceCaseManager(caseManager2) \quad \text{(O-31.c)}$$

OWL 32 (Advocacy Help Properties)**.**

which goal?
$$hasGoal(chf3, getHelpResolvingCriticalIssues3) \quad \text{(O-32.a)}$$
Why do they want it? the need?
$$triggeredBy(getHelpResolvingCriticalIssues3, needToReduceStress3) \quad \text{(O-32.b)}$$
how is it ranked?
$$prefAgent(getHelpResolvingCriticalIssues3, 4) \quad \text{(O-32.c)}$$
motivation?
$$describedMotiveFor(resolveCriticalConflictsWithLandlord3, getHelpResolvingCriticalIssues3) \quad \text{(O-32.d)}$$
$$expressedBy(resolveCriticalConflictsWithLandlord3, chf3) \quad \text{(O-32.e)}$$
what's constraining them?
$$constrainedBy(getHelpResolvingCriticalIssues3, lackOfConflictResSkills3) \quad \text{(O-32.f)}$$
what resource is needed?
$$requiredBy(resourceCaseManager3, lackOfConflictResSkills3) \quad \text{(O-32.g)}$$
what services provides the resource?
$$createdBy(resourceCaseManager3, caseManager3) \quad \text{(O-32.h)}$$
which service was accessed?

$$accessedBy(caseManager3, chf3) \tag{O-32.i}$$

6.3.5 Mapping Conditional Goals In OSSN

Conditional goal-mapping requires some agent-specific condition to identify which MH level a requested need is mapped to. Unlike the directly mapped goals for clothing and advocacy, conditional mappings are inferred from the intersection of an agent's demographic and its specific need.

Temporary Housing

Consider a request for "temporary housing" at some shelter. Such requests are categorized differently for absolutely and relatively homeless clients. For absolutely homeless clients it is a physiological **MH need**, while for the relatively homeless it is a security **MH need**. In OSSN an agent's homeless state is a demographic defined by axioms O-18 and O-19 for absolutely and relatively homeless respectively. For both types of homeless agents, the **MH goal** is to find "temporary housing shelter" **motivated** by wanting "temporary housing for a short time." The requested **goal** is "get help to find temporary housing." The **constraint** faced by such clients is that they do not know which beds are available, and in which shelters. The **resource** is a temporary bed available at a shelter. The **service** is a social worker that can help them find a bed by providing required knowledge. How the MH goal is mapped to an MH level is inferred from the agent's homeless state and goal type.

First, the class $GoalForAbsHomeless$ is any goal that is requested by an absolutely homeless agent, as per axiom O-33. Second, a request for temporary housing, say $getTempHousing2$, is asserted as $GoalTempHousing(getTempHousing2)$.

OWL 33 (GoalForAbsHomeless Class)**.**

$$GoalForAbsHomeless \equiv \exists hasGoal^{-}.AbsHomelessAgent \tag{O-33}$$

Mapping the temporary housing goal to the physiological MH level is conditional on the agent being absolutely homeless. First we define the class $MHGoalTempHousingPhysiological$ as the subclass of $MHGoalPhysiological$, as per axiom O-34.a. Next we define the condition for this agent demographic and goal type as the intersection between goals requested by absolutely homeless clients and temporary housing goals, as per axiom O-34.b.

OWL 34 (MHGoalTempHousingPhysiological Class)**.**

$$MHGoalTempHousingPhysiological \sqsubseteq MHGoalPhysiological \tag{O-34.a}$$

$$\begin{aligned} MHGoalTempHousingPhysiological \sqsubseteq\ & MHGoalPhysiological \sqcap \\ & \exists triggeredBy^{-}.GoalForAbsHomeless \sqcap \\ & \exists triggeredBy^{-}.GoalTempHousing \end{aligned} \tag{O-34.b}$$

Finally, temporary housing goals requested by a relatively homeless agent are mapped to the security level. Similarly to the physiological temporary housing goal, the $MHGoalTempHousingSecurity$ class is defined as the subclass of $MHGoalSecurity$ in axiom O-35.a. Next, the conditional mapping of relatively homeless agent and temporary housing goal are a subclass of the newly defined security-level temporary housing need, as per axiom O-35.b.

OWL 35 (MHGoalTempHousingSecurity Class)**.**

$$MHGoalTempHousingSecurity \sqsubseteq MHGoalSecurity \tag{O-35.a}$$

$$MHGoalTempHousingSecurity \sqsubseteq MHGoalSecurity \sqcap \exists triggeredBy^{-}.GoalForRelHomeless \sqcap \exists triggeredBy^{-}.GoalTempHousing \quad \text{(O-35.b)}$$

The following assertions implement this scenario in OWL for $chf2$, an absolutely homeless agent.

OWL 36 (Housing Temp Need Classes for Absolutely Homeless)**.**

$$AbsHomelessAgent(chf2) \quad \text{(O-36.a)}$$
$$GoalTempHousing(getTempHousing2) \quad \text{(O-36.b)}$$
$$ConstraintTempHousing(lackOfInfoTempHousingBed2) \quad \text{(O-36.c)}$$

OWL 37 (Housing Temp Need Classes for Absolutely Homeless)**.**

$$hasGoal(chf2, getTempHousing2) \quad \text{(O-37.a)}$$
$$triggeredBy(getTempHousing2, needTempHousingShelter2) \quad \text{(O-37.b)}$$
$$prefAgent(getTempHousing2, 2) \quad \text{(O-37.c)}$$
$$describedMotiveFor(needTempHousingForShortStay2, getTempHousing2) \quad \text{(O-37.d)}$$
$$expressedBy(needTempHousingForShortStay2, chf2) \quad \text{(O-37.e)}$$
$$constrainedBy(getTempHousing2, lackOfInfoTempHousingBed2) \quad \text{(O-37.f)}$$
$$requiredBy(resourceTempBed2, lackOfInfoTempHousingBed2) \quad \text{(O-37.g)}$$
$$createdBy(resourceTempBed2, socialWorker2) \quad \text{(O-37.h)}$$
$$accessedBy(socialWorker2, chf2) \quad \text{(O-37.i)}$$

Child Care

A conditional mapping can also be based on the explicit request made by the agent, rather than its demographics. For example, a client requesting help for child services will specify the type of service being requested based on needs of their child. The MH level it is mapped to depends on the MH level for the child's need it is requested for. According to OSSN mapping, if the agent's **MH goal** is to have a "happy family" and their **motivation** is to have "socially adjusted kids," this is an esteem-level **need**. The concrete **goal** being requested might be "toys, activities, education, and counselling for kids." The **constraint** belongs to the agent not the child, and is a "lack of money and activities." **Resources** to relieve the constraint may include "holiday presents," "youth advocacy," or "charity." "Family service" is the required **service** provider.

OWL 38 (Example Child Care Esteem Individuals)**.**

$$GoalChildCare(getChildToysActivitiesEducationCounselling2) \quad \text{(O-38.a)}$$
$$MHGoalHappyFamilyEsteem(needHappyFamilyEsteem2) \quad \text{(O-38.b)}$$
$$ConstraintChildCare(lackOfMoneyActivities2) \quad \text{(O-38.c)}$$
$$ServiceFamilyServices(familyServices2) \quad \text{(O-38.d)}$$

OWL 39 (Child Care Esteem Properties)**.**

$$prefAgent(getTempHousing2, 3) \quad \text{(O-39.a)}$$
$$describedMotiveFor(haveSociallyAdjustedKids2, getChildToysActivitiesEducationCounselling2) \quad \text{(O-39.b)}$$
$$expressedBy(haveSociallyAdjustedKids2, chf2) \quad \text{(O-39.c)}$$
$$constrainedBy(getChildToysActivitiesEducationCounselling2, \quad \text{(O-39.d)}$$

$lackOfMoneyActivities2)$

$requiredBy(resourceCharity2, lackOfMoneyActivities2)$ (O-39.e)

$requiredBy(resourceHolidayPresents2, lackOfMoneyActivities2)$ (O-39.f)

$requiredBy(resourceYouthAdvocacy2, lackOfMoneyActivities2)$ (O-39.g)

$createdBy(resourceCharity2, familyServices2)$ (O-39.h)

$createdBy(resourceHolidayPresents2, familyServices2)$ (O-39.i)

$createdBy(resourceYouthAdvocacy2, familyServices2)$ (O-39.j)

$accessedBy(familyServices2, chf2)$ (O-39.k)

Child care may also be a security-level **need**. Here, the **MH goal** is to provide basic child care like basic "protection and security," and excludes emergency situations. The **motivation** is to meet the child's "basic protection and security needs." The requested **goal** is a summary of things a child may need any one time to satisfy their "basic needs and provide tangible goods to keep the child safe." The **constraints** are most often than not lack of money. Often a charity will provide for such non-emergency goals, hence "charity" is the **resource**. "Family services" is the **service** provider that connects a client to the applicable charity. The agent $chf2$ decided to access family services, as per assertions O-40 and O-41.

OWL 40 (Example Child Care Security Individuals)**.**

$GoalChildCare(getBasicNeedsGoodsForChild2)$ (O-40.a)

$MHGoalChildProtectionSecurity(needChildProtectionSecurity2)$ (O-40.b)

$ConstraintChildCare(lackOfMoney2)$ (O-40.c)

$ServiceFamilyServices(familyServices2)$ (O-40.d)

OWL 41 (Child Care Security Properties)**.**

$hasGoal(chf2, getBasicNeedsGoodsForChild2)$ (O-41.a)

$triggeredBy(getBasicNeedsGoodsForChild2, needChildProtectionSecurity2)$ (O-41.b)

$prefAgent(getBasicNeedsGoodsForChild2, 4)$ (O-41.c)

$describedMotiveFor(protectKids2, getBasicNeedsGoodsForChild2)$ (O-41.d)

$expressedBy(protectKids2, chf2)$ (O-41.e)

$constrainedBy(getBasicNeedsGoodsForChild2, lackOfMoney2)$ (O-41.f)

$requiredBy(resourceCharity2, lackOfMoney2)$ (O-41.g)

$createdBy(resourceCharity2, familyServices2)$ (O-41.h)

$accessedBy(familyServices2, chf2)$ (O-41.i)

Finally, any emergency or critical needs of a child are mapped to the physiological level **need**, as it is deemed as important as basic nutrition- and health-related needs. The **MH goal** is simply "physiological need of kids." The **motivation** for the parent is to "keep kids healthy," while the concrete **goal** is to "provide emergency child care needs." The **constraint** is the "lack of money or information." To relieve the constraint, a service may again utilize a **resource** by referring clients to one of two services, a charity that specializes in child-specific needs or a social worker. The **service** provider can be one of two providers: family services that provide charity or a social worker, or in extreme cases, child protective services that provide a social worker. In the example defined below, the agent decided to access child protective services, as per assertions in O-42.

OWL 42 (Example Child Care Physiological Individuals).

$$GoalChildCare(getEmergencyChildCare2) \tag{O-42.a}$$
$$MHGoalChildBasicPhysiological(needChildBasicPhysiological2) \tag{O-42.b}$$
$$ConstraintChildCare(lackOfMoneyInfo2) \tag{O-42.c}$$
$$ServiceChildProtectiveServices(childProtectiveServices2) \tag{O-42.d}$$

OWL 43 (Child Care Physiological Properties).

$$hasGoal(chf2, getEmergencyChildCare2) \tag{O-43.a}$$
$$triggeredBy(getEmergencyChildCare2, needChildBasicPhysiological2) \tag{O-43.b}$$
$$prefAgent(getEmergencyChildCare2, 5) \tag{O-43.c}$$
$$describedMotiveFor(keepKidsHealthy2, getEmergencyChildCare2) \tag{O-43.d}$$
$$expressedBy(keepKidsHealthy2, chf2) \tag{O-43.e}$$
$$constrainedBy(getEmergencyChildCare2, lackOfMoneyInfo2) \tag{O-43.f}$$
$$requiredBy(resourceCharity2, lackOfMoneyInfo2) \tag{O-43.g}$$
$$requiredBy(resourceSocialWorker2, lackOfMoneyInfo2) \tag{O-43.h}$$
$$createdBy(resourceCharity2, familyServices2) \tag{O-43.i}$$
$$createdBy(resourceSocialWorker2, familyServices2) \tag{O-43.j}$$
$$createdBy(resourceSocialWorker2, childProtectiveServices2) \tag{O-43.k}$$
$$accessedBy(childProtectiveServices2, chf2) \tag{O-43.l}$$

6.3.6 Mapping Unconditional Goals In OSSN

Many OSSN needs are mapped to multiple MH levels at once. For example, wanting clean clothes is mapped to security, social, and esteem MH-level needs. Other requests are by default mapped to multiple levels, but may also depend on the agent's progress. For example, the need to fight addiction is a short- and long-term goal mapped to physiological and self-actualization levels respectively. If the agent is just beginning, the request is mapped to both levels. However, if the agent is far enough along in its detox program, its request is a long-term goal, mapped only to the self-actualization level. The following two examples demonstrate these use-cases.

Clean clothes

Having "clean clothes" is a request that impacts a client at multiple MH level **needs**, namely security, social, and esteem. Each MH level is mapped to the same **MH goal** to "feel safe with other people," as defined by O-45.d. The goal "clean clothes" spans multiple MH levels, not just security, because it impacts elements of each level, as defined by O-44.c to e. It is also mapped to the social level because it negatively impacts the agent's interactions with others. Finally, clean clothes is mapped to the esteem level because it impacts clients' comfort with themselves, as well as their ability to interact and be positively perceived by others. The **constraint** faced by the agent is that it does not have money to pay for its own laundry. The **resource** is free laundry service they can access. Finally, the **service** provider is a shelter that is offering free laundry service.

OWL 44 (Example CleanClothes Individuals).

$$GoalCleanClothes(getLaundryCleanClothing4) \tag{O-44.a}$$
$$ConstraintCleanClothes(lackOfMoneyLaundry4) \tag{O-44.b}$$
$$MHGoalCleanClothesSecurity(feelSafeWithOthers4) \tag{O-44.c}$$

$$MHGoalCleanClothesSocial(feelSafeWithOthers4) \tag{O-44.d}$$
$$MHGoalCleanClothesEsteem(feelSafeWithOthers4) \tag{O-44.e}$$
$$ServiceLaundry(shelter4) \tag{O-44.f}$$

OWL 45 (Clean Clothes Properties).

$$hasGoal(chf4, getLaundryCleanClothing4) \tag{O-45.a}$$
$$triggeredBy(getLaundryCleanClothing4, feelSafeWithOthers4) \tag{O-45.b}$$
$$prefAgent(getLaundryCleanClothing4, 6) \tag{O-45.c}$$
$$describedMotiveFor(cleanClothing4, getLaundryCleanClothing4) \tag{O-45.d}$$
$$expressedBy(cleanClothing4, chf4) \tag{O-45.e}$$
$$constrainedBy(getLaundryCleanClothing4, lackOfMoneyLaundry4) \tag{O-45.f}$$
$$requiredBy(resourceLaundry4, lackOfMoneyLaundry4) \tag{O-45.g}$$
$$createdBy(resourceLaundry4, shelter4) \tag{O-45.h}$$
$$accessedBy(shelter4, chf4) \tag{O-45.i}$$

Stay sober

Staying sober is a special type of multi-MH unconditional goal. The ultimate goal of requesting support is to become and stay sober, a long-term goal. As discussed in Section 6.2.1, self-actualization goals sometimes act as motivators for goals in other levels. In the case of addiction, it is the motivation and willpower to get through the intermediate steps of getting over withdrawal symptoms. Such symptoms are physiological level needs. Hence, to stay sober is both a self-actualization and physiological **need**. The short-term physiological goals for fighting addiction, defined in assertions O-46 and O-47, have an **MH goal** of becoming healthy. The **goal** is to find help getting sober. The **motivation** is a combination of the two, to get sober and become healthy. The **constraint** is a lack of determination and self-discipline to invest the time to seek out and sign up in a recovery program. The **resource** is a counsellor who meets with the client to determine their level of need and most appropriate services. Finally, the **service** is a detox program the client can enrol in.

OWL 46 (Example Short-Term Addiction Individuals).

$$GoalAddiction(helpGettingSober3) \tag{O-46.a}$$
$$MHGoalAddictionPhysiological(becomeHealthy3) \tag{O-46.b}$$
$$ConstraintAddiction(lackOfDeterminationSelfDiscipline3) \tag{O-46.c}$$
$$ServiceDetox(detoxProgram3) \tag{O-46.d}$$

OWL 47 (Short-Term Addiction Properties).

$$hasGoal(chf3, helpGettingSober3) \tag{O-47.a}$$
$$triggeredBy(helpGettingSober3, becomeHealthy3) \tag{O-47.b}$$
$$prefAgent(helpGettingSober3, 6) \tag{O-47.c}$$
$$describedMotiveFor(getSoberAndBeHealthy3, helpGettingSober3) \tag{O-47.d}$$
$$expressedBy(getSoberAndBeHealthy3, chf3) \tag{O-47.e}$$
$$constrainedBy(helpGettingSober3, lackOfDeterminationSelfDiscipline3) \tag{O-47.f}$$
$$requiredBy(resourceCounsellor3, lackOfDeterminationSelfDiscipline3) \tag{O-47.g}$$
$$createdBy(resourceCounsellor3, detoxProgram3) \tag{O-47.h}$$
$$accessedBy(detoxProgram3, chf3) \tag{O-47.i}$$

Long-term addiction goals are similar to short-term goals, but focus more on keeping the client motivated to stay sober and completing post-detox tasks. Hence, staying sober is a self-actualization **need**. The **MH goal** focuses on "staying healthy," with a **goal** of "staying sober." The **motivation** is to maintain sobriety and a healthy life style, but also becoming self-reliant. The **constraints** these clients face include lack of determination and self-discipline, as well as a lack of awareness of services. The **resource** to overcome these constraints is meeting with a counsellor who provides motivation and missing information about required programs. This resource is provided by a **service** that focuses on post-detox programs.

OWL 48 (Example Long-Term Addiction Individuals).

$$GoalAddiction(staySober3) \quad \text{(O-48.a)}$$
$$MHGoalAddictionSelf(stayHealthy3) \quad \text{(O-48.b)}$$
$$ConstraintAddiction(lackOfDeterminationSelfDiscipline3) \quad \text{(O-48.c)}$$
$$ServiceDetox(postDetoxProgram3) \quad \text{(O-48.d)}$$

OWL 49 (Long-Term Addiction Properties).

$$hasGoal(chf3, staySober3) \quad \text{(O-49.a)}$$
$$triggeredBy(staySober3, stayHealthy3) \quad \text{(O-49.b)}$$
$$prefAgent(staySober3, 7) \quad \text{(O-49.c)}$$
$$describedMotiveFor(staySober3, maintainSoberAndHealthy3) \quad \text{(O-49.d)}$$
$$expressedBy(maintainSoberAndHealthy3, chf3) \quad \text{(O-49.e)}$$
$$constrainedBy(staySober3, lackOfDeterminationSelfDiscipline3) \quad \text{(O-49.f)}$$
$$requiredBy(resourceCounsellor3, lackOfDeterminationSelfDiscipline3) \quad \text{(O-49.g)}$$
$$createdBy(resourceCounsellor3, postDetoxProgram3) \quad \text{(O-49.h)}$$
$$accessedBy(postDetoxProgram3, chf3) \quad \text{(O-49.i)}$$

6.4 OSSN Evaluation

OSSN was evaluated by constructing formal competency questions for the informal competency questions in groups 1, 2, and 3 listed in Section 6.1.6. The questions are implemented as queries in the SPARQL[4] query language. The Pellet [5] Reasoner Plug-in version 2.2.0 was used to identify and explicitly assert all class, object property, data property, and individual inferences found in OSSN. These inferences were exported into a single ontology file, included in Appendix D. SPARQL Query Plugin 2.0.2 [6] was used to execute each query.

The results are presented in Appendix D.1. Overall, the ontology performs well on groups 1 and 2, which relate to client and service types. The relationship between clients and their goals is well represented, where SPARQL is able to answer queries about demographics and goals. OSSN is also capable of answering queries about service provisioning. It captures the relationships between client

[4]SPARQL Query Language for RDF: *https://www.w3.org/TR/2008/REC-rdf-sparql-query-20080115/*
[5]Pellet Reasoner: *https://www.w3.org/2001/sw/wiki/Pellet*
[6]SPARQL Query Plugin 2.0.2: *https://github.com/protegeproject/sparql-query-plugin/releases/tag/sparql-query-plugin-2.0.2*

demographics and the use of certain services. By relying on the *Outcome* class, OSSN can answer some performance queries that relate to a program and its participants. Any questions with a temporal dimension are not handled well by OSSN. The rate at which resources are used or when they become unavailable is not captured by the ontology. While an extension to the *Resource* object can be made that captures inventory and availability, the temporal dimension required to capture changes in either metric is not available.

The questions in group 3 relate to the process of decision making. They evaluate the ontology's ability to identify patterns in the data and casual relationships between entities. OSSN was not designed to make such inferences. While relations between entities are captured, they are limited to static definitions. An evaluation of the process of decision making is outside the scope of OSSN. Question Q-30 ("What interim goals are required to satisfy goal X?") can be answered by generating a plan using the action schema *AS* and STRIPS-BR planner. However, evaluation of the planner is outside the scope of this chapter. The remaining questions, Q-31 to Q-37, require either a simulated execution of a plan to evaluate replanning, or inquire about the emotional changes that occur during plan execution. Such analysis is addressed in Chapter 7.

6.5 Discussion

The motivating scenarios proposed in Section 6.1.1 identified the scope and focus for the development of the ontology of social service needs. While the main goal of this thesis is to evaluate social service provisioning, the objective is to perform this analysis using a high-fidelity client model. OSSN is an ontological representation of what motivates a client and how they rank their goals, and OSSN is developed based on the data included in the CHF-HF dataset, grounding each request in the data to one of 58 request categories mapped to an MH level.

Relying on goal semantics introduced in Chapter 3, OSSN identifies the semantics required to associate a BRAMA agent's needs with the services they use. The relations included in OSSN allow a domain expert to model an agent as a client identified in the CHF dataset. OSSN includes the entities required to represent a BRAMA agent as a social service client, including its MH needs, goals, motivations, and constraints preventing goals from being satisfied. The service provider is represented from the agent's perspective. The focus is placed on how the service can relieve constraints exhibited by the agent, which resources are required, and which services provide those resources. By putting the focus on the client's needs, the agent's decisions are not centred around service efficiency, but on satisfying the underlying constraints clients face. This ensures that not just the needs, but also the agent's limitations are the focus of any emulated decision making.

Grounding OSSN terms in CHF-HF data allows the representation of real clients as BRAMA agents. Data provided by HF Assessment forms captures a client's needs. Since needs were collected every three months, the data also captures how a client's needs change over time. By mapping client needs to MH levels, OSSN allows a BRAMA agent to identify how it ranked its goals in relation to our understanding of needs based on Maslow's hierarchy.

OSSN allows the extrapolation of factors that may have led to a goal listed in the data, and the emulation of decisions based on actions associated with those goals and action constraints. A subject matter expert can then create an action schema that BRAMA can use to emulate a client's behaviour. Depending on the agent's demographics, certain conditional goals are mapped to specific MH levels. For directly mapped goals, there is a one-to-one relation between goals and MH levels. For conditionally mapped goals, the mapping is inferred from the semantics captured by OSSN and the agent's demographics. For unconditionally mapped goals, OSSN can map a goal to multiple MH levels.

Finally, OSSN was developed using the ontology engineering methodology of Grüninger and Fox [101], in which competency questions provided a way to evaluate how well it can answer certain questions. For OSSN, the formal questions are provided in the SPARQL query language. Queries and their results successfully answered questions about clients, their demographics, goals, motivations, and goal ranking. Queries about service providers, the types of clients they serve, and goals they satisfy were also successfully answered. However, any questions that asked about the process of satisfying goals were not successfully answered. These questions require the simulation of agents as they interact with service providers and respond according to their goals and model $\mathbb{M}$ configuration.

6.6 Conclusion

This chapter extends BRAMA by introducing the ontology of social service needs (OSSN), which identifies the semantic relations between an agent's needs, motivations, and explicit requests made to a service provider. The ontology also connects each request with the final services that satisfy the goals underlying each request. It is the first ontological representation of social services from the agent's perspective, filling in a significant gap in the social service domain. From the agent's perspective, the main connection to services is the constraints preventing agents from satisfying their goals. The service provider's responsibility is to define specific actions required to remove such constraints, based on the available services and resources. The actions provide a sequence of steps an agent must complete within a particular instance of a social service system. The ontology was evaluated by answering certain competency questions. The questions that were not answered require a simulation to emulate how an agent changes its goals.

By extending the BRAMA system to incorporate OSSN and the action schema, a variety of agent configurations can be created that emulate the behaviour of clients. Grounding OSSN needs and services in those identified in the CHF-HF data potentially allows for the emulation of participants represented by different BRAMA agent configurations. The CHF dataset gives us the goals clients requested. The action schema provides possible steps required to satisfy those goals. What is not known is the internal factors that influence an agent's decision making. The $\mathbb{M}$ model captures these factors and the possible configurations a BRAMA agent can represent that influence decision making. Hence, the final step in the development of BRAMA is the simulation of BRAMA agents capable of emulating the behaviour of actual social service clients. The CHF data can again be used to configure a BRAMA agent model $\mathbb{M}$. OSSN is used to map each request identified in CHF data to an MH level, whether direct, conditional, or unconditional. The action schema developed for services included in OSSN can be used to emulate an agent's plan generation phase, within their limitations defined by a configuration $\mathbb{M}$. During the execution phase, the agent's emotional evaluation of plan execution can be evaluated. Chapter 7 undertakes this work. The agent model's behaviour is simulated with different $\mathbb{M}$ configurations. Each configuration results in selection of plans and replanning of goals in unique ways. Finally, the simulated behaviour is measured on how well it matches the actual trajectories of CHF-HF participants.

Chapter 7

Evaluation

7.1 Introduction

This chapter introduces and summarizes results for two series of experiments that evaluate the fidelity of the BRAMA framework. The complete experiment report is provided in Appendix E.5. This report is the last of five experiments conducted as part of this thesis. The remaining reports are provided in Appendices E.1, E.2, E.3, and E.4.

The main hypothesis introduced in Chapter 1 stated that seemingly “irrational” behaviour can be emulated using a rational reasoner. The experiments presented here attempt to confirm or deny this hypothesis by testing six sub-hypotheses that collectively ask which components of a cognitive model are sufficient to create a cognitive model of a human-like agent. Human-like agents are represented as Housing First participants from a study conducted by the Calgary Homeless Foundation (CHF-HF). The experiments are designed as fractional-factorial experiments modelled after Barton [16]. Each cognitive component in $\mathbb{M}$ represents an independent variable. Each combination of independent variables is a different test configuration. The results of the experiments indicate that human-like factors do produce trajectories that more closly resemble actual trajectories found in data than trajectories produced by a rational agent that simply maximizes utility. There are two key conclusions of the experiments. First, some form of replanning is required to emulate the changing needs of clients. Second, emotional components emulate replanning and goal reranking more accurately than simply relying on bounded rationality exhibited by an agent.

Determining whether a model is sufficiently accurate is based on two metrics. The first metric is the accuracy with which a simulated trajectory using a model $\mathbb{M}$ can match an actual trajectory in the CHF-FH dataset. The second metric is an error threshold that defines what is considered a sufficient “match.” The error selected is the mean absolute error (MAE) between actual and simulated requests of an agent. Given the mean MAE for an entire model across all trajectories, accuracy measures how well the model performed in identifying a match, given an MAE threshold.

As the baseline model, we begin with a classically rational model with boundless cognitive resources and a neoclassical evaluation function that maximizes utility. Through a series of experiments, the model is incrementally modified by adding human-like cognitive components introduced in this thesis. For each new model, the rational goal reasoner STRIPS-BR introduced in Section 5.4 is used to generate and select plans. The simulation in Section 5.7 is used to emulate how such an agent’s behaviour may change while interacting with its environment. This simulated behaviour is compared to the real behaviour found in the CHF-HF data.

As was discussed in Chapter 4, one of the objectives of this work was to identify factors that were observable by a bounded observer. Hence, in addition to the rationality of a model, the evaluation of experimental results incorporates the degree to which each factor is observable. Factors that are easier to observe are preferred over those that are harder to observe. For example, BRAMA's representation of cognitive and time bounds are an approximation for the subject's actual cognitive limitations. As these are difficult characteristics to capture explicitly they are less observable than other factors. A decision strategy is a proxy to the level of commitment and foresight someone expresses about their long-term decisions. For example, they may have limited foresight (myopic), perfect foresight (resolute), or be risk-neutral (sophisticated). The strategy a subject uses may be inferred by evaluating the subject over an extended period of time. The emotional cycle of change (ECOC) threshold is a proxy for the subject's emotional state. Since emotions are often expressed externally, the threshold may be observed if sufficient trust exists between the subject and the observer. Also, the preferred ranking of goals may be observable if the order of requests matched the agent's preferences. Provided the service constraints are known, the practical order is observable through scheduling constraints placed on the service providers. Finally, Maslow's order is assumed to be observable by applying the domain-specific mappings presented in Chapter 6 to observed requests made by clients.

7.1.1 Hypothesis

The purpose of experiments presented here is to answer our main hypothesis:

Main hypothesis: Seemingly "irrational" behaviour can be emulated using a rational reasoner.

To test this hypothesis, six sub-hypotheses are tested. These are split between two series of experiments. Series 1 experiments address hypotheses 1 to 5:

Hypothesis-1: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with bounded rationality limits than without.

Hypothesis-2: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with plan utility maximization than without.

Hypothesis-3: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with myopic and sophisticated search strategies than without.

Hypothesis-4: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with Maslow's hierarchy as preferred goal ranking than without.

Hypothesis-5: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when maximizing ECOC expected utility than when maximizing the neoclassical expected utility function.

Series 2 experiments address hypothesis 6:

Hypothesis-6: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when replanning based on ECOC threshold than replanning based only on bounded rationality limits.

7.1.2 Experiment Design

This section introduces the experiments, their goals, design, and evaluation criteria.

Experiment Goals

The goals of the experiments presented here are to prove each sub-hypothesis. The metric for each experiment identifies factors that, with high accuracy, reduce the difference between time series data provided by CHF and simulation trace produced by BRAMA. In Figure 7.1 the goal hierarchy is presented. This experiment provides details about levels 5 to 7.

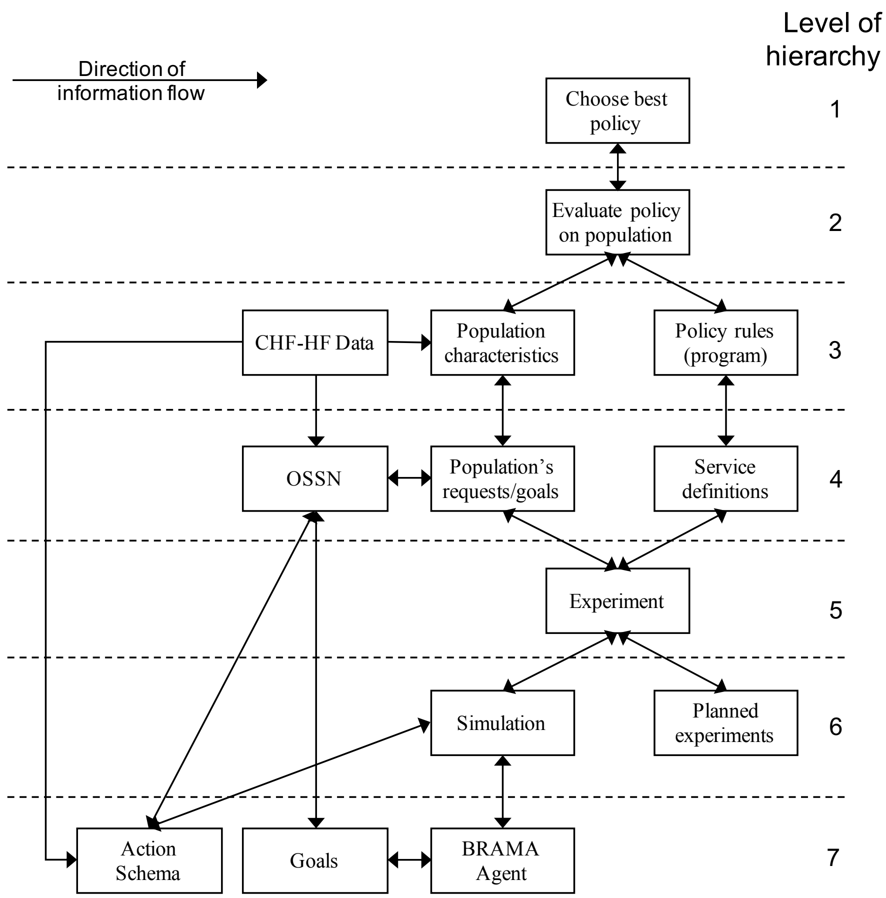

Figure 7.1: Experiment goal hierarchy for social service policy evaluation

The overall goal of the project at level 1 is to choose the best social service policy for the target population. At level 2, an evaluation of policy on a given population is performed. At level 3, population characteristics and the policy's rules under a specific program are identified. Since this is implementation specific, a dataset is provided. In the context of this experiment, the dataset provided by Calgary Homeless Foundation (CHF) about their Housing First (HF) program is referred to as CHF-HF. At level 4, a population's requests/goals and the services they use are defined. The requests/goals are categorized according to the ontology of social service needs (OSSN). At level 5 a series of experiments is defined. At level 6 the simulation environment and experimental design are defined. The points of interaction between the simulation and experiments are the variables and test configurations used for the experiments. Finally, at level 7 the BRAMA framework provides the models used to execute simulations for each experiment. It includes an action schema and goals created using OSSN. It also includes the BRAMA agent which is in part defined by the goals along with other variables, as discussed in the next section.

Experiment Design

The experiments have a fractional-factorial design. Factor levels are the values that each factor can take. Factorial experiments are based on a grid, where each factor value is tested in combination with values of every other factorial. For example, a two-level factor will have two values, say low and high, or -1 and 1. Unlike a factorial experiment, a fractional-factorial experiment has factors with different levels. For example, an experiment may have a mix of two-level and three-level factors. The experiments introduced in this chapter are eight-factor designs that use eight independent variables listed in Table 7.2. The design contains three two-level factors (*planutil*, *executil*), four three-level factors ($BR(C)$, $BR(T)$, *pref*), and two four-level factor (*strategy*, *ecoc-th*).

Variables

Dependent variables listed in Table 7.1 are those that are being tested. These include the simulated trace of goal counts and periods as well as the metrics used to evaluate models. The metrics for each model includes the accuracy of finding a match and the error threshold for defining a sufficient match.

Table 7.1: Dependent variables

Variables	**Values**	**Description**
Simulated goal trajectory	Goal count per period	Sum of goals at each MH level for each period in the simulated trajectory.
AE_{mh}	$\{0, 1, 2, 3, \ldots\}$	Absolute error for Maslow's level mh between the number of goals in actual and simulated periods.
MAE_{mh}	$\{0, 1, 2, 3, \ldots\}$	Mean absolute error (MAE) for Maslow's level mh of each agent in a model. MAE is used for comparing goal trajectories in the simulation trace to goal trajectory from CHF-HF data, defined in Equation 7.2. MAE represents the mean number of goals the actual and simulated trajectories differed by.
MAE_k	$\{0, 1, 2, 3, \ldots\}$	Mean absolute error of each agent in some model $\mathbb{M}$ for agent k. It is used for comparing the overall errors between goal trajectories in the simulation trace to goal trajectory from CHF-HF data, defined in Equation 7.3.
$MAE_{\mathbb{M}}$	$\{0, 1, 2, 3, \ldots\}$	MAE for a model $\mathbb{M}$ configuration across all agents.
MAE-threshold	$\{0, 1, 2, 3, \ldots\}$	MAE threshold for determining a cutoff for a good model.
Number of True Positives (TP)	$\{0, 1, 2, 3, \ldots\}$	Agent k with: $MAE_k \leq$ MAE-threshold and ($MAE_{\mathbb{M}}$ + 0.25) $\leq$ MAE-threshold.
Number of True Negatives (TN)	$\{0, 1, 2, 3, \ldots\}$	Agent k with: $MAE_k >$ MAE-threshold and ($MAE_{\mathbb{M}}$ + 0.25) $>$ MAE-threshold.

Table 7.1: Dependent variables

Variables	Values	Description
Number of False Positives (FP)	$\{0, 1, 2, 3, \ldots\}$	Agent k with: $MAE_k \geq$ MAE-threshold and $(MAE_{\mathbb{M}}$ + 0.25) > MAE-threshold.
Number of False Negatives (FN)	$\{0, 1, 2, 3, \ldots\}$	Agent k with: $MAE_k >$ MAE-threshold and $(MAE_{\mathbb{M}})$ + 0.25) $\leq$ MAE-threshold.
True Positive Rate	$[0, 1]$	TPR = TP / (TP + FN), or 0 if (TP + FN) is equal to 0.
False Positive Rate	$[0, 1]$	FPR = FP/(FP+TN) , or 0 if (FP + TN) is equal to 0.
accuracy	$[0, 1]$	Given an MAE threshold, the accuracy of a model $\mathbb{M}$ in matching simulated trajectory to the actual trajectories, as per Equation 7.1.

Independent variables listed in Table 7.2 are the factors that control each experiment configuration. These are the factors being evaluated for their impact on accuracy and MAE. Baseline values are used for a model configuration on which the proposed higher fidelity model configurations must improve on. When appropriate, the baseline model uses a special postfix label "-bsln" for factor values, such as *strategy* = *resolute-bsln*, meaning that this is the baseline model and its strategy is resolute. A complete description of each variable is provided in Chapter 5.

Table 7.2: Independent variables

Variables	Values (actual quantity)	Description
Actual goal trajectory	goal count per period	Sum of goals at each MH level for each cycle in the actual trajectories in CHF-HF dataset.
$BR(C)$	*h-bsln* (no limit), m (70), l (40)	Cognitive bound is defined as the maximum depth of a search tree, defined as *h-bsln* for "high" used for baseline, m for "medium," and l for "low."
$BR(T)$	*h-bsln* (30,000), m (10,000), l (5,000)	Time bound is defined as the maximum number of states visited in a search tree, defined as *h-bsln* for "high" used for baseline, m for "medium," and l for "low."
planutil	*none*, *planutilswap*	Plan selection criteria during the planning phase where none means select first plan found and *planutilswap* means find plan with highest utility.
strategy	*myopic*, *soph*, *resolute*, *resolute-bsln*	Planning strategy including myopic, sophisticated, resolute, and "resolute-bsln."

Table 7.2: Independent variables

Variables	**Values** (actual quantity)	**Description**
pref	*agent*, *MH*, *agent-bsln*	Preference used by the agent during the execution phase, where agent means the agent's preferred order, MH means Maslow's order, and *agent-bsln* means baseline also uses the agent order.
execu	$exp, ecoc$	Expected utility function used during the execution phase.
ecoc-th	$0.0, 0.1, 0.2, 0.4, 0.6$	ECOC threshold for triggering replanning. For *ecoc-th* = 0.0, replanning is not triggered due to ECOC but instead due to other factors.
action-th	$0.0, 0.1, 0.3, 0.6$	Action utility used to select goals for deferment.

7.1.3 Data

The Calgary Homeless Foundation (CHF)[1] has provided a dataset that captured information about clients as they participate in a Housing First (HF) intervention program administered by the CHF and its partner service providers. The CHF-HF dataset contains information on approximately 4,000 individual clients that participated in the HF program in Calgary from 2009 to 2015. Data continued to be collected through 2016. The information was collected using the HF Assessment questionnaires found on the CHF website [2]. For this analysis, 2,094 participants were included between 2012 and 2015. The dataset is summarized here, with a complete description and analysis provided in Section 6.1.2.

Participant Selection Process

CHF used the following process for selecting participants.

1. Various "intake" forms are provided every time a client comes into a shelter participating with CHF in the Calgary region.
2. Among them, the Service Prioritization Decision Assistance Tool (SPDAT) questionnaire is administered to clients in the Calgary region. SPDAT is a tool to assess a social service client's acuity. The answers provided by clients are self-reported with the help of service providers. These are not clinically verified.
3. A group of organization and intervention program administrators review each newly filled out SPDAT form from the Calgary region to decide whether a client is suitable for their service offering from the intervention program.
4. The HF program selects participants that have a high acuity level, indicating they are good candidates for the level of independence required by the program.

[1] The Calgary Homeless Foundation: *http://calgaryhomeless.com/*, accessed November 21, 2016.
[2] CHF forms: *http://calgaryhomeless.com/what-we-do/oversee-hmis/user-information-tools/hmis-forms/* , accessed November 21, 2016.

Data Gathering Procedures

CHF used the following procedure to gather data.

1. Once a client is selected for the CHF-HF program, they are contacted and a process for finding suitable housing begins.

2. Once housing is found, the client is relocated to the new location and given the move-in HF Assessment form: "Move-in-Assessment (v 7.27.2015)".

3. A follow-up HF Assessment questionnaire is administered every 3 months: "General-HS-HF-3-60-Month-Follow-Up-Interview (v 10.16.2015)".

4. When a client exits the program, successfully or otherwise, an exit HF Assessment form is administered: "Exit-Assessment (v 7.27.2015)".

Action Schema Creation

Of the 58 request types represented by OSSN, an action schema was created for the 22 request types listed in Table 7.3. Of the 2,094 CHF participants, 43 participants were selected that only requested one or more of these 22 request types.

Table 7.3: Requests types from OSSN included in the tests

Employment training	Income
Utility arrears	Clothing
Moving	Rent arrears
Tenant insurance support	Health support
Debt reduction	Housing temp
Disability support	Clean Clothing
Medication	Hygiene
Security deposit	Addiction support
Identification	Child care
Housing supplement	Rent shortfall subsidy
Furniture	Food

Agent Configuration

In the test environment, different combination of factors were created. In total, 133 different test configurations were created, one for each $\mathbb{M}$ configuration. Each test configuration was conducted for each of the 43 agents, resulting in $133 \times 43 = 5,719$ individual experiment runs. Each configuration is a stand-alone test. For each test, an error score is computed that identifies how closely the goal preferences of a simulated agent match those of its actual counterpart in the dataset. For each test, each of the 43 agents was initialized with the requests made by its actual counterpart in the CHF-HF dataset. This initial goal set includes all requests the actual participant made for all three-month periods, and in the order given. All goals were included in the initial goal set. Any distribution of goals over multiple periods was done solely by the replanning and reranking algorithm.

Client Needs Trajectory

In addition to capturing a client's basic needs, HF Assessment also provides a trajectory of those needs over time. Section 6.1.3 discusses the comparison between basic needs at move-in and follow-up interviews. Follow up interviews at three-month intervals capture client needs as a time-series dataset. At each three-month interval, HF Assessment captures all the requests a client makes to the service provider. Figure 7.2 provides an example client with needs at each MH level from intake at time 0 up to the 12-month HF Assessment follow-up.

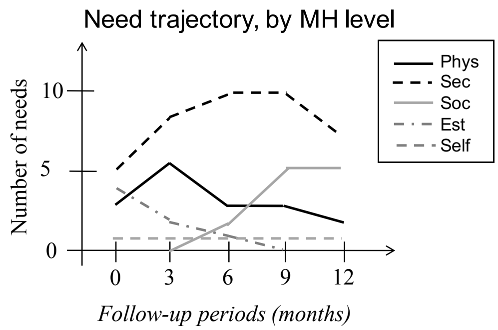

Figure 7.2: Example need trajectory of an agent from intake at time 0 to follow-up at 12

The horizontal axis lists different time points a HF Assessment questionnaire was administered. The move-in and follow-up data points are approximations for actual needs of the participants, as per the discussion in Section 6.1.3. The vertical axis is the total number of requests made at each time point, summed for each MH level. For example, during intake at time 0, the client requested three physiological needs, five security needs, zero social needs, four esteem needs, and one self-actualization need. At month three, the client's physiological needs increased from three to five needs, security to seven needs, esteem needs dropped to two needs, and self-actualization needs remained at one. At month six, the client requested their first two social needs, saw a decrease of physiological needs, and a continued increase in their security needs. Throughout the trajectory, the client's esteem needs decreased over time to zero, while self-actualization needs remained at one.

The number of needs can also be aggregated by combining time periods. For example, during the first six months, the client requested eleven physiological needs (three at move-in, five at three months, and three at six months). After six months the client requested an additional five physiological needs. In total, the client requested 16 physiological needs in the first 12 months of the CHF-HF program. Aggregate needs will be discussed further in Section 7.1.5.

7.1.4 Experiment Limitations

There are several limitations placed on the experiments that impact the testing of the hypotheses. These include limitations of the data provided by CHF and computational limitations of the simulation.

Data-Based Limitations

The main hypothesis states that seemingly irrational individuals are acting rationally but within human-centric limitations. As discussed in Section 1.1, the limitation of using data in the homeless domain is the constraint that only observable factors can be reliably used to configure an agent that emulates human-like behaviour. Several limitations are placed on the BRAMA agent which are meant to replicate the limitations placed on clients captured by CHF-HF data. However, not all factors are observable or captured by the data.

Client demographics and requests for basic needs are provided by the CHF data. The causal order of each request is represented as a trajectory of requests. Its order is based on the order HF Assessment questionnaires were administrated in, whether at move-in, during follow-up visits, or during the exit interview. The simulations generate several trajectories using different configurations of the agent model, and match the simulated trajectories to those of the actual trajectories found in CHF data. Since only requests and demographics are provided, additional social science theories of behaviour are used to supplement the models with domain-specific modifications.

The ontology of social service needs (OSSN) introduced in Chapter 6 relies on client demographics and basic needs to best align those requests with Maslow's hierarchy. The client's actual preferred ranking of goals is not provided. Instead, the experiments assume that the requesting order is the preferred order. It is also not known if the services required to meet those needs are provided and utilized by the client. It is assumed that they have been, and that unless the request is made again in a future questionnaire, the service was successfully utilized to satisfy the client's needs. The cognitive limitations of clients are also not provided. Hence, the exact bounds exhibited by clients is not known. Different configurations of bounds are evaluated to find ones that produce trajectories that match trajectories found in the data.

The emotional state of the clients is not provided. This makes it difficult to confirm whether a client is in fact in a pessimistic or an optimistic ECOC stage or whether they are following the neoclassical utility function. Instead, the assumption is made that if a simulated trajectory matches the actual trajectory, the specified utility function matched the client's characteristic. When the neoclassical expected utility produces the best match, emotions are assumed to not have played a role in the actual client's decision making. If the ECOC utility is used to produce the best results, then emotions are assumed to have influenced the client's decision making. Finally, the action schema identified in Appendix C and used in the simulation does not necessarily match that of the CHF service providers. Best efforts were made to ensure that a reasonable representation is captured.

Decision strategies used by CHF participants are not provided. Instead, simulated trajectories with a low MAE are used to identify which client may be using a myopic or sophisticated strategy to change goals, and which are using the resolute strategy to keep goals static. In Series 2, it is assumed that goal reranking and replanning are based on emotions or bounded rationality, and only the resolute strategy is used.

Finally, the time frames for simulated trajectories are not known. While actual periods are three months apart, what happens within each time frame is not known. Hence, simulated periods may span more than one period, or multiple simulated periods may span a single actual period. Aggregate periods discussed in Section 7.1.5 are meant to compensate for these discrepancies.

Simulation Limitations

Due to computational limitations, several limits were placed on the simulation execution time. First, a time limit of 60 minutes was placed on each configuration. Fifteen configurations were excluded from the experiment analysis due to this constraint. Second, any simulation with an agent configuration that required more than 44 periods for the simulation to finish were excluded from experiments, and are identified as “agerr” in the result tables in Appendix E.4.2. In total, 14 agents were impacted and partially represented, across 81 simulation.

Finally, due to limited execution time and available memory on the test machine, limitations were placed on how large a search tree was possible. This made it difficult to generate and evaluate different utility functions and preferred orders that required a large search tree. For example, the “unbounded” time and cognitive abilities for the baseline agent model were in fact bound with a high number to ensure the generated search tree was large enough to find many solutions while finishing within a reasonable amount of time and fit within the memory constraints of the test computer. Hence, not all possible plans were included in the tree and assigned a plan utility. Within the limits, variability in goal and action order was observed at the end of each plan, which produced small variations in overall plan utility. As a result, there was no significant difference between plan utility and selected plans between models that used different factor configurations. The affected factors include the agent’s preferred order ranking ($pref = agent$) to calculate utility versus Maslow’s goal ranking ($pref = MH$), the use of neoclassical utility function ($execu = exp$) versus ECOC-based function ($execu = ecoc$), and models that maximize utility ($planutil = planswaputil$) versus models that choose the first plan found ($planutil = none$). In these cases, the initial order of goals played a more significant role than the plan utility in finding a plan that maximized plan utility.

7.1.5 Experiment Metrics

The metrics described here are used to determine whether a model $\mathbb{M}$ produces simulated trajectories that match actual trajectories found in the data. The accuracy score determines how well a model matches agent configurations included in the test. Accuracy is calculated by

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{7.1}$$

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

Next, we must determine what is considered a sufficient condition for trajectories to be a match. For this, the distance between the number of goals in actual versus simulated periods is used to calculate the error between two trajectories. The error threshold, then, defines what is considered a match. The indicator used to calculate the error is the number of goals per Maslow’s level that an actual and simulated agent has at a given point in time. The error selected is the mean absolute error (MAE) between real requests made and simulated requests of an agent. Originally mean squared error was used as the error metric. The mean absolute error was chosen instead due to many outlier errors that skewed the results. Finally, the mean[3] $MAE_{\mathbb{M}}$ for an entire model across all trajectories is calculated, and accuracy then measures how well the model $\mathbb{M}$ performed in identifying a match, given an MAE threshold.

Mean Absolute Error

The difference between simulated and actual trajectories is calculated as the mean absolute error (MAE) between the number of goals of all periods in each trajectory. Consider again the trajectory of actual

[3] The mean of mean absolute errors $MAE_{\mathbb{M}}$ is taken for each model $\mathbb{M}$.

physiological needs in Figure 7.2. In Figure 7.3, the actual trajectory of physiological needs is shown again, along with the simulated trajectory of physiological needs. Each follow-up period represents the beginning and end of a cycle. A cycle represents the time an agent took to satisfy its goals. The absolute error (AE) is the difference between actual and simulated number of physiological goals at each time point between cycles.

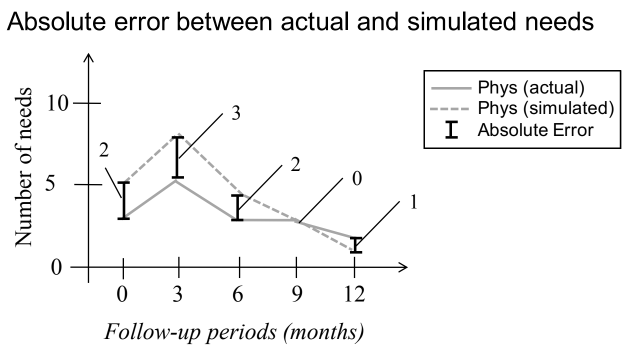

Figure 7.3: Example absolute error between actual and simulated trajectory for physiological needs

To calculate the error for the entire trajectory of needs for an MH level mh, the mean of all absolute errors at that level is taken as the mean absolute error MAE_{mh} defined by

$$MAE_{mh} = \frac{\sum_{i=1}^{n} |G_i^{act} - G_i^{sim}|}{n}, \tag{7.2}$$

where mh is one of the five MH levels, $i \in \{1, \ldots, n\}$ is the period index, n is the number of time periods between cycles, and G_i^{act} and G_i^{sim} are the sum of actual and simulated goals outstanding at period i, respectively.

$$MAE_k = \frac{\sum_{mh=1}^{5} MAE_{mh}}{5} \tag{7.3}$$

To calculate the MAE between actual and simulated trajectories for all levels of an agent's needs, the mean of MAE_{mh} for all levels is calculated as MAE_k for some agent $k \in K$ from agent set K, as per Equation 7.3.

$$MAE_{\mathbb{M}} = \frac{\sum_{k \in K} MAE_k}{|K|} \tag{7.4}$$

Finally, $MAE_{\mathbb{M}}$ for a model $\mathbb{M}$ configuration is the mean of all MAE_k for agents $k \in K$ in the model, as per Equation 7.4.

Aggregate Mean Absolute Error

An aggregate MAE is one that uses aggregate periods to calculate the absolute error between actual and simulated periods. Aggregate periods are those that combine multiple periods, as explained next. Recall that the MAE considers the difference between the number of actual and simulated goals at each period. However, as mentioned in Section 7.1.4, the actual length of a cycle and time between each period is domain- or situation-specific. For example, an actual client may take one day, a week, or a month to consistently satisfy their goals. They then move onto other goals that may or may not be satisfied when the three-month period is over. The three-month period is simply a constraint enforced by the CHF-HF program. As a result, the data only shows a snapshot of what needs were unsatisfied for that cycle. Hence, while a simulated agent completes goals in one cycle, that cycle may represent one week, a month, a three-month period, or two periods that last six months in total.

To compensate for the three-month constraint of the study, and the lack of information about how long each simulated cycle lasts in actual calendar time, an aggregate of absolute errors per period is calculated.

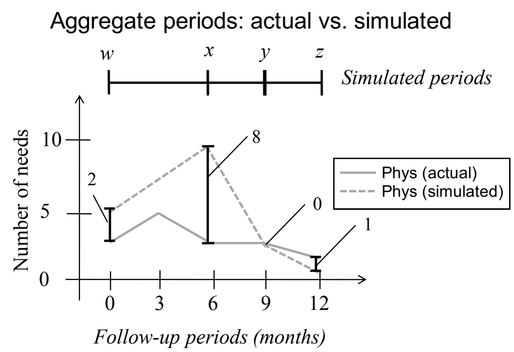

Figure 7.4: Example of aggregate periods

Consider the actual and simulated trajectories in Figure 7.4. In this example, the number of goals outstanding in the actual trajectory at each period are three goals at month 0, five at month 3, three at months 6 and 9, and two goals at month 12, with the trajectory being four cycles in total. The simulated trajectory, however, is made up of only three cycles to satisfy the same goals. The number of outstanding goals at each simulated period are five goals at period w, ten at the period x, three at period y, and one goal at period z.

Aggregate periods combine multiple periods for calculating an absolute error. For example, the simulated cycle from periods w to x overlaps with actual periods at months 0, 3, and 6. The absolute error for physiological goals AE_{phys} between periods 0 and w is not aggregated and is the same as in Figure 7.3, namely $AE_{phys} = |5 - 3| = 2$. To calculate the difference between simulated period x and its actual counterpart, actual periods 3 and 6 must be aggregated by summing their goals. The result is the actual aggregated goal number, namely $5 + 3 = 8$. To calculate AE_{phys}, this sum is subtracted from simulated period x, giving the aggregate $AE_{phys} = |10 - 8| = 2$. For the remaining periods y with 9 and z with 12, AE_{phys} is calculated without aggregation. MAE_{phys} is then calculated as per Equation 7.2, where n is the smaller number between simulated and actual periods. Different combinations of actual and simulated aggregate and non-aggregate trajectories are used to align best pairs. The pair with lowest MAE_{mh} is chosen for calculating MAE for an agent MAE_k and the entire model $MAE_{\mathbb{M}}$.

7.2 Hypothesis Testing

In this section, each set of experiments is evaluated to identify whether each hypothesis was confirmed or denied. Determining whether a model is sufficient is based on two metrics. First is the *accuracy* of the model, which indicates the model's ability to successfully identify a match between actual and simulated trajectories. The second is an MAE threshold that defines what is considered a "match." Different MAE thresholds were used and the accuracy of each model evaluated.

7.2.1 Series 1 Hypotheses

Figure 7.5 presents the accuracy of different $\mathbb{M}$ configurations using a subset of the factors, at different MAE thresholds for Series 1 experiments. The models along the horizontal axis are sorted by their accuracy score for MAE thresholds of 2.0.

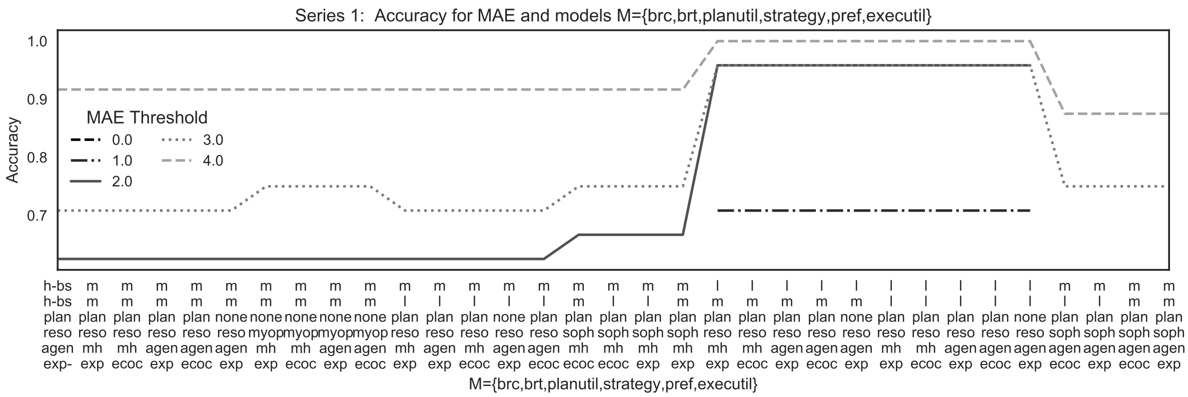

Figure 7.5: Series 1 MAE for each threshold, sorted by MAE threshold 2.0

With an MAE threshold of 0.0 no results are produced, meaning no model matched the agent's goals perfectly. With an MAE threshold of 1.0, we see that only models $\mathbb{M}$ with $BR(C) = l$ (low) and $strategy = resolute$ produced results that matched actual trajectories. However, the highest accuracy achieved was 0.7 for these models. With an MAE threshold of 2.0, these same models simulate trajectories that match actual trajectories with accuracy of 0.95. In fact, these models have the highest accuracy at this MAE threshold. This result indicates that a low $BR(C)$ and resolute strategy are the best factors for emulating actual clients. The resolute strategy itself is not sufficient, since the baseline model, identified by $BR(C) = h\text{-}bsln$ (shortened to *h-bs* in the graph), has low scores. The only distinguishable feature of models with highest accuracy is the low $BR(C)$.

The main takeaway from Series 1 results is that a low $BR(C)$ limit, with a maximum search tree depth of 40 actions, produces the most accurate results. Also, some form of replanning is required to create a good match of human-like behaviour for selected clients from the CHF-HF dataset. However, it is not sufficient to force replanning at every time step by using the myopic or sophisticated strategy. Instead, a combination of a resolute strategy and a low $BR(C)$ ensures that shorter partial plans are executed that satisfy a subset of goals per execution cycle.

The results for Series 1 experiments have direct implications for hypotheses 1 to 5.

Hypothesis-1: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with bounded rationality limits than without.

The baseline model configuration represents a rational agent in the neoclassical sense. It has high bounds, uses the neoclassical utility function ($execu = exp$) and the agent's preferred goal ranking ($pref = agent$). As demonstrated in Figure 7.5, baseline is in the group of models with the lowest accuracy for all MAE thresholds.

The models with a low $BR(C)$ had the highest accuracy for all MAE thresholds. The time bound $BR(T)$ along with other factors did not seem to impact accuracy in any significant way.

Hence, hypothesis 1 is confirmed that bounded agents, specifically those that have a low cognitive bound, produce a better emulation than those without.

Hypothesis-2: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with plan utility maximization than without.

There is no significant difference between models that maximize utility ($planutil = planswaputil$; shortened to *plan* on the graph) versus those that do not ($planutil = none$). This is a result of computational limitations placed on the experiments, as discussed in Section 7.1.4.

Hence, no conclusion can be made for hypothesis 2 is denied.

Hypothesis-3: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with myopic and sophisticated search strategies than without.

It is difficult to compare performance of models that used the resolute strategy to those that used either myopic or sophisticated. Computing limitations prevented models with sophisticated strategy and $BR(C) = l$ from finishing execution, and were excluded from the result. Models with the myopic strategy were not impacted by bounded cognition since only immediate actions were evaluated and there was no need to create a large search tree.

Two observations can be made from these results. First, models with the resolute strategy perform better than those with myopic strategies. Second, models with the sophisticated strategy require higher $BR(C)$ bounds or longer computation time to find at least one plan than either the resolute or myopic strategies. Combining both observations, the resolute strategy has the best performance within the computational limitations. The myopic strategy had more completed plans within the agents bounds. Also, the sophisticated strategy had the worst performance of all three strategies. These results also show that replanning due to a low $BR(C)$ rather than due to myopic or sophisticated strategies produces results with higher accuracy.

Hence, hypothesis 3 is denied, and better performance is achieved with the resolute strategy over myopic and sophisticated, especially when combined with a low cognitive bound.

Hypothesis-4: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with Maslow's hierarchy as preferred goal ranking than without.

There is no significant difference between models that use Maslow's hierarchy ($pref = mh$) versus those that do not ($pref = agent$). This again is a result of computational limitations placed on the experiments, as discussed in Section 7.1.4.

Hence, no conclusion can be made for hypothesis 4 is denied.

Hypothesis-5: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when maximizing ECOC expected utility than when maximizing the neoclassical expected utility function.

There is no significant difference between models that use a neoclassical utility function ($execu = exp$) versus those that use an ECOC utility function ($execu = ecoc$). This again is a result of computational limitations placed on the experiments, as discussed in Section 7.1.4.

Hence, no conclusion can be made for hypothesis 5 is denied.

7.2.2 Series 2 Hypothesis

Figure 7.6 presents the accuracy of different $\mathbb{M}$ configurations at different MAE thresholds for Series 2 experiments. The models along the horizontal axis are again sorted by their accuracy score for MAE thresholds of 2.0. All models in Series 2 rely on $strategy = resolute$, $planutil = planswaputil$, and ECOC utility function. These are omitted from the horizontal axis. The time bound $BR(T)$ was found to not be significant and is also omitted. The cognitive bound $BR(C)$ along with action and ECOC thresholds *action-th* and *ecoc-th* are included.

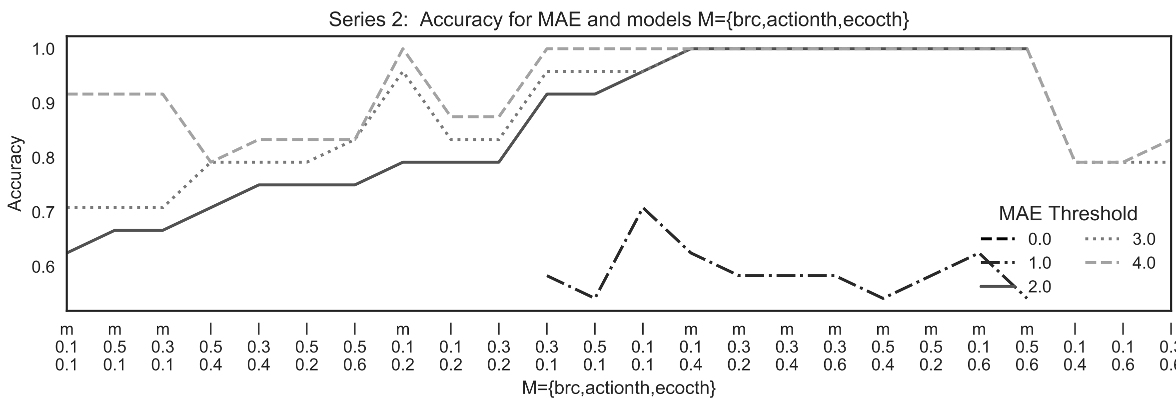

Figure 7.6: Series 2 MAE for each threshold, sorted by MAE threshold 2.0

As in Series 1, with an MAE threshold of 1.0 we see a partial list of models that were matched and produced an accuracy score. These are split into two groups, where $BR(C) = l$ (low) and where $BR(C) = m$ (medium). Where $BR(C) = l$, *ecoc-th* has a low value of 0.1, while for $BR(C) = m$ the threshold *ecoc-th* has values greater than 0.1. The action threshold *action-th* has no significant impact on accuracy.

Not surprisingly, when the MAE threshold is 2.0 more models have matches and are visible on the graph. The same pattern is found as discussed in the previous paragraph. Models with $BR(C) = l$ and lower *ecoc-th* have lower accuracy while models where $BR(C) = m$ and *ecoc-th* is greater have higher accuracy.

These results indicate again that plans with replanning produce better accuracy. With a low $BR(C)$, replanning is caused by the cognitive bound. With a medium $BR(C)$ there is less need to replan as a result of cognitive limitations. Hence, where $BR(C) = m$, replanning occurs due to higher *ecoc-th*. The question that answers whether hypothesis 6 is confirmed or denied now depends on whether replanning due to ECOC (with a higher threshold) has higher accuracy than bounded rationality (with a low $BR(C)$).

The results for Series 2 experiments have direct implications for hypothesis 6.

Hypothesis-6: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when replanning based on ECOC threshold than replanning based only on bounded rationality limits.

In Series 1 tests, best results were produced due to replanning caused by low $BR(C)$ bounds. In Series 2 experiments, replanning was caused by either low $BR(C)$ or the *ecoc-th* threshold where a medium $BR(C)$ was used.

Accuracy for models where $BR(C) = l$ with low *ecoc-th* threshold on average produce models with lower accuracy score. Where *ecoc-th* = 0.1, accuracy is between 0.8 and 0.95, with the vast majority of models falling at or below 0.9. Accuracy for models where $BR(C) = m$ with a high *ecoc-th* (greater than 0.2) on average produce models with a higher accuracy score of 1.0.

Hence, hypothesis 6 is confirmed: models with ECOC produce more accurate emulation than those with cognitive bounds only.

7.3 Evaluation and Discussion

The main hypothesis of this thesis states that seemingly "irrational" behaviour can be emulated using a rational reasoner. By "irrational," this thesis means behaviour that is actually rational but exhibited by a bounded subject and perceived by a bounded observer. Using data identifying demographics and requests made by a Housing First program participants, this chapter attempted to identify the factors that may cause a participant, the subject, to exhibit behaviour that a neoclassical rational but bounded observer may deem irrational. By identifying these factors, and confirming or denying the sub-hypotheses, the objective was to show that there are rational reasons for a subject exhibiting the behaviour, and that the underlying factors may not be obvious to the observer. Due to the nature of the problem and target domain, namely evaluating use of social services by clients experiencing homelessness, the number of requests made by clients at specific time intervals are a proxy for how clients change their goal preferences over time and how they respond to limitations on service providers. The needs were grouped and ranked into levels of Maslow's hierarchy with the use of the ontology of social service needs (OSSN) introduced in Chapter 6. The ontology allowed for a mapping between requests made by clients in the data and levels of the hierarchy, which were based on the type of request and the client's demographics.

Relying on a rational reasoner, six sub-hypotheses were tested by extending the original rational model with human-like factors. The results of the experiments indicate that some form of replanning is required to emulate the changing needs of clients, and some replanning triggers are easier to observe than others. Tests for three of the six hypotheses were inconclusive due to computational limitations. To evaluate models, the *accuracy* metric was used to rank how well a model $\mathbb{M}$ can match changing needs of actual clients. The criteria of what constitutes a match is based on the mean absolute error (MAE) threshold, with different thresholds being tested. A sufficient MAE threshold was deemed to be 2.0, meaning the model can predict the number of goals to within an average between 1.0 and 2.0 and no more than 2.25 goals per period. Acceptable models were those with a high accuracy rate and low MAE threshold.

Hypothesis 1 is evaluated by stating that extending a rational reasoner with bounded rationality would produce models with higher accuracy. This was confirmed when models with a low cognitive bound had higher accuracy than baseline, which had no bounds. Since baseline has no replanning, and low cognitive bound forces some replanning, replanning was deemed a key characteristic that a classically rational agent does not exhibit, but is nevertheless required for emulating the targeted populations. A classically rational agent is assumed to be omniscient, knowing everything that is required to make and execute a successful plan without replanning.

Hypothesis 2 is evaluated by stating that extending a rational reasoner with utility maximization would produce better results. Due to computational limitations discussed in Section 7.1.4, certain limits were placed on the size of the search tree that could be built using low or medium cognitive and time bounds. Unfortunately, due to these bounds, the search tree was not large enough, and did not consider a sufficient variety of plans to differ greatly in expected utility. For this reason, no conclusion can be made and hypothesis 2 was denied.

For hypothesis 3, the model was extended with myopic and sophisticated strategies to test whether a model with these strategies can emulate “irrational” behaviour better than the resolute strategy used up to now. Unlike the resolute strategy, myopic and sophisticated strategies perform replanning at every time step. It was shown that the combination of bounded rationality and resolute strategy emulated actual behaviour with higher accuracy than either of the other two strategies. However, the sophisticated strategy with a low cognitive bound did not complete due to computational limitations. Hence, no conclusion can be made and hypothesis 3 was denied, leading to the conclusion that a combination of bounded rationality and a resolute strategy was required to produce most accurate results.

Hypothesis 4 is evaluated by stating that extending the models with Maslow’s hierarchy to rank goals would produce more accurate results. The rationale behind this was that Maslow’s hierarchy, given a domain-specific mapping, would better reflect how the utility of goals change during execution than without the hierarchy. Due to computational limits, the search tree was again not sufficiently large to contain the required number of plan variations to produce significantly large differences in plan utility. Within the limits, variability was observed at the end of each plan, which produced small variations in overall plan utility. Hence, it was not possible to confirm the hypothesis, which was then denied. It was concluded, however, that due to this type of limitations, plans in the search tree were more dependent on the initial goal order (based on the agent’s preferred order) and the practical order enforced by the action schema and action preconditions.

Hypothesis 5 is evaluated by stating that extending the models with an expectation function based on ECOC would produce more accurate results than with neoclassical function used in previous tests. Again, due to computational limitations, a sufficiently large search tree was not generated to produce sufficient variability in plan utilities. Hence, no conclusion can be made and hypothesis 5 was denied.

Finally, hypothesis 6 is evaluated by stating that extending the model with a replanning trigger based on ECOC expected utility would produce more accurate results than using bounded rationality alone. By defining different ECOC thresholds for an executable plan utility, it was shown that models that trigger replanning due to the ECOC threshold do produce emulation with higher accuracy than with bounded rationality alone, or no replanning at all. As a result, hypothesis 6 is confirmed, and replanning with ECOC emulates human-like agents better than relying solely on bounded rationality.

Chapter 8

Observations and Conclusion

8.1 Introduction

In this chapter, observations about social services in the context of the BRAMA system are discussed, followed by a summary of the contributions. This chapter concludes with a description of future research extending work presented here, and possible research into some of the limitations of the system.

The contributions of this thesis are in three areas: AI search, representation, and emulation of social service clients. In the AI search area, a planning algorithm extends an existing algorithm by incorporating human-centric features. This work includes:

- Evaluation of applicable decision theories and their limitations.
- A framework for emulating seemingly "irrational" behaviour grounded in decision theories.
- Explicitly defined limitations based on bounded rationality.
- Goal ordering and utility calculation grounded in Maslow's hierarchy.
- Utility calculation based on the emotional cycle of change.
- Replanning algorithm to overcome bounded rationality with the use of emotional thresholds.
- Human-like goal reasoning.

In the representation area, an ontology of social service client needs is created based on goals expressed by participants in a real-life intervention program. The ontology captures basic needs, explicit goals, initial goal ranking expressed by clients, and constraints preventing clients from satisfying their goals. A domain-specific mapping is made between client needs and Maslow's hierarchy, grounding goal ranking in a psychological theory of needs. The ontology also captures the resources and services offered by service providers that relieve the constraints faced by clients.

The contribution to social services is the first client-focused ontology of the social service system. The objective is to capture how certain client populations will react to an intervention program. By focusing on the clients, they are presented as rational beings, with a unique set of constraints that may lead an observer to mischaracterize rational behaviour as "irrational." Finally, the ontology makes an explicit distinction between services offered and social programs that administer them. This allows a program administrator to track the outcomes of participants independently from service providers.

8.2 Observations and Conclusions

Several key insights were observed in the duration of this thesis. These are presented here.

8.2.1 Experiment Conclusion Summary

The experiment evaluated in Chapter 7 was the last in a series of five experiments conducted using the CHF-HF dataset. The four previous experiments incrementally investigated what can and cannot be used to predict or emulate aspects of seemingly “irrational” behaviour exhibited by CHF-HF participants. This section summarizes each experiment, with the complete experiment reports provided in Appendix E. The initial evaluation of CHF-HF data is described in Appendix A. The type of evaluation performed is based on the evaluation conducted by Volk et al. for the At Home/Chez Soi (AH-CS) program, which calculated the p value for each attribute captured about program participants at intake [257]. Experiments 2 through 5 incorporate the temporal dimension by introducing changing needs of CHF-HF participants. Adair et al. also incorporated a temporal dimension for analysis of AH-CS participants [2]. This work relied on statistically derived patterns of latent variables to predict client outcomes.

Experiment 1 in Appendix E.1 was modelled after the evaluation conducted by Volk et al., and extended with needs of participants mapped to Maslow’s hierarchy. In [257], the main question asked was: “Can we predict, at admission, the characteristics of individuals who will continue to experience housing instability after one year in the HF program?” In addition to calculating the p value, predictive analysis was performed using a hierarchical logistic regression model for clients’ status after 12 months in the program. Experiment 1 asked the same question and performed similar analysis on the CHF-HF data. The p value was calculated for each demographic attribute captured about the clients at intake. Rather than relying on a single predictive model, this experiment used a factorial experiment design, modelled after Barton [16], to test different combinations of classification models and demographic attributes to predict client outcomes. As in Volk et al., each classifier saw minor improvements in accuracy over guessing “success” versus “failure” at random. Clients that had treated and untreated mental health problems saw an improvement of 4.8%. An improvement of 3.8% of clients was observed based on their first language being English.

Experiment 2 in Appendix E.2 extends the models in Experiment 1 by predicting client outcomes with changing needs of clients as they participate in the program. Needs are mapped to Maslow’s hierarchy and the number of needs in each MH level at different points in time were incorporated into the model. Similar to the predictive model by Adair et al. on AH-CS data [2], the incorporation of changing needs over time introduced a time dimension to the predictive model. The experiment again uses a factorial-experiment design and tests different configurations of classification models, demographics, and the participants’ changing needs. The results of the experiment show that predictions using the client’s needs along with key demographics see an additional improvement of 3% over demographics alone, as per Experiment 1. Adair et al. also concluded that, while no explicit predictor was found, some classes of trajectories were dominated by certain demographics, highlighting a potential correlation [2]. However, no prediction about outcome for particular individuals could be made.

Experiment 3 in Appendix E.3 extends the prediction of client outcomes by introducing a simulated progression through the emotional cycle of change (ECOC). Relying on a state machine, clients progress through ECOC stages based on the changes in their needs for each MH level. In addition to the state-machine, a reinforcement learning algorithm adjusts the weights for each stage of ECOC required to transition client agents from one stage to anther.

The increase in accuracy using ECOC stages was not as high as was expected. It should be noted that by relying only on transitions in ECOC stages, predictions with higher accuracy were made when compared to using demographics alone. Also, relying on transitions through ECOC stages plus only the 'MentalProb-k' demographic produced the highest precision score at 76%. This is an increase of 9% over only the 'MentalProb-k' demographic, and a 4% increase over 'MentalProb-k' plus needs mapped to MH levels.

Experiment 4 in Appendix E.4 tests a new hypothesis, namely whether, despite seemingly "irrational" behaviour, a client's exit period from a program can be predicted better when considering their changing needs in a program rather than just demographics at intake. The purpose of Experiment 4 was to find a model capable of predicting *when* a client will exit an intervention program rather than their *actual* exit status. As with previous experiments, the independent variables are the client's MH needs and demographics. The dependent variable is the client's exit period. The predictive model is a recurrent neural network with long short-term memory unit, a module made specifically for time-series data. Here, the client's changing needs are represented as a time-series dataset. In addition to the client's demographics, the short-term memory unit has a single input neuron for each time point in the series, namely a three-month interval, and the number of needs per MH level. The results are compared to those produced by traditional classifiers using demographic information only.

Based on the result, the experiment shows that the hypothesis is proven true and that by considering certain demographics and changes in MH needs, it is possible to predict exit periods in the CHF-HF intervention program with higher precision than other classifiers that do not consider changing needs of clients as a time-series. The changes in MH goals in combination with key demographics are a valid predictive measure over just using demographics at baseline. Good predictions can be made after the six-month time period. Based on the low precision score at the three-month period, it is hypothesized that the three-month period is a particularly dynamic period for clients, as it is the most difficult to predict. Comparing these results to Adair et al. and Volk et al. [2, 257], we conclude that while there is no significant correlation between program outcomes and variables like participant demographics and changing needs, these variables may indicate when a participant will exit, successfully or not. This may serve as an indicator for preemptive analysis of an individual client.

Experiment 5 is the final experiment, as presented in Chapter 7, with a complete experiment report in Appendix E.5. The main hypothesis introduced in Chapter 1 stated that seemingly "irrational" behaviour can be emulated using a rational reasoner. Experiment 5 includes a series of experiments that attempt to confirm or deny this hypothesis by testing six sub-hypotheses. These sub-hypotheses collectively ask which components of a cognitive model are sufficient to create a cognitive model of a human-like agent. The experiments are designed as fractional-factorial experiments modelled after Barton [16]. The results indicate that human-like cognitive components do produce trajectories that closer resemble actual trajectories found in the data. There are two key conclusions for Experiment 5. First, some form of replanning is required to emulate the changing needs of clients. Second, emotional components emulate replanning and goal reranking more accurately than simply relying on bounded rationality exhibited by an agent.

8.2.2 Limitations of Social Service Evaluation

The first and main observation coming out of this work is the acknowledgement that the evaluation of social services is a difficult process. The work presented in this thesis depended on the collection and verifiability of reliable data. Due to limitations of obtaining such data, practitioners and researchers must rely on various methods and theories to qualify the observations they make. Data captured as interviews with clients contains information that is sufficiently detailed, but the sample size tends to be too small to perform analysis that is statistically significant. When datasets are sufficiently large, the types of questions that can expect reliable answers tend to be too general for detailed analysis. Recent studies have been focused on larger sample sizes with detailed questionnaires and coding schemes. However, the data collected and conclusions made tend to be focused on specific factors that may not apply to an entire population.

Until this data becomes available and accessible, the metrics for evaluating social service policy will be limited to qualitative analysis by experts in the field, combined with statistical analysis of trends and projections. Many of the observations discussed here aim to highlight areas where methods in artificial intelligence and industrial engineering can help in client-focused analysis. The main takeaway is that rather than applying statistical analysis to data at intake, understanding a client's changes as they participate in an intervention program is beneficial, and AI methods can be used to understand such changes.

For the evaluation of BRAMA models, insufficient data about client emotions prevented this aspect of the model from being validated. As with other studies in the social service domain, sample size used to make the final models were small. Much care must be taken and more detailed data about services must be available to apply these models to evaluate specific individuals and programs.

8.2.3 Social Service Representation

A secondary objective of this thesis has been to capture the nature of services provided to clients. The various services offered by social service providers have been captured before. The overall objective of this previous work can be categorized as some combination of modelling, understanding, and optimizing the existing system. The reasons for focusing mostly on the service provider vary from budget cuts and reorganization to projected growth in volume of clients. As discussed in Section 1.1.1, such objectives view the system from the perspective of the service provider. As a result, any study that focuses on client progress assumes service provisioning is working optimally. This may result in insufficient client progress to be prematurely associated with unknown client-specific issues. In BRAMA, the lack of real-life service delivery data limited the validation process to changes in client choices. Any removal of previously requested services was assumed to be a result of those services being successfully applied.

The action schema presented in Appendix C and the ontology of social service needs (OSSN) provide a view of the service provider from the client's perspective. To achieve this, the goal-to-service mappings in OSSN are based on my own lived experience working in the social service field and analysis performed with subject matter experts. The approach was to begin identifying real client needs first, and then mapping required services to those needs. This approach abstracted away details not visible to clients, focusing instead on the constraints clients face when using services. These may include missing resources, required order of services, and alternative services available to and known by the client.

By focusing on client needs rather than available services, different aspects of a client's needs are identified and explicitly characterized. For example, social needs incorporate the client's community and identify what needs can be satisfied by their social network. In such cases, an alternative to a service provider should factor in the client's choices and the way providers arrange complementary services. For example, data about aboriginal-specific services was not available. To compensate for this, a "catch-all" service is defined in OSSN that outsources assistance to specialized providers within the aboriginal community. An extension to OSSN and the action schema could focus on the priorities of this community. Such an extension would likely identify bottlenecks in the way more general services interact with specialized ones.

8.2.4 Client Representation as an Agent

The emulation of client behaviour is as much a "social good" topic as an interesting technical problem. It required the identification and characterization of basic concepts like goals and preferences in a way that accurately captured homeless client behaviour. As introduced in Section 1.1.1 and expanded on in Section 2.5, assumptions about the target population's needs that were no longer true required a complete reevaluation. Behaviour was viewed from a new perspective, with a focus on different factors than used previously.

One of the challenges of the work presented here was the lack of data about the more fundamental factors that influence client behaviour. Structural factors were available from existing research, but the analysis was generally done in the context of specific scenarios and client circumstances. BRAMA benefited greatly from such research, but it required constant contact with subject matter experts in the respective fields. Generalizing such analysis continues to be an active research area within social services [121, 7, 18].

To overcome some of the data limitations, the need to capture easily observable data became a research focus in its own right. An observer's perception of a client became a factor in defining the agent and interpreting available data. The creation of a high-fidelity model capable of representing the complexity of a homeless client became contextualized in the society within which they live. This served two purposes. The first and more obvious purpose was to identify external factors impacting the homeless population, a standard requirement for modelling any agent within a system. The second purpose was the recognition and utilization of social norms in the qualification of a homeless population's behaviour. By clearly categorizing different views about interpreting human behaviour and to what ends, competing views from sociology, psychology, economics, and AI were combined. This was necessary to interpret and combine research about behaviour from each of these disciplines. The resulting agent model captured what could be extracted from available data, incorporating various theories of behaviour and behaviour change.

8.2.5 Search

Emulation of client behaviour is represented as an AI planning problem. As a result, defining how such a problem is represented and solved in a way that emulates a homeless client highlighted several key limiting design decisions in the AI field. The emulation of seemingly "irrational" behaviour is in stark contrast to existing work. Rather than focusing on efficiently finding optimal solutions, BRAMA required the reproduction of inefficient and seemingly non-optimal behaviour due to human limitations and impediments.

Being limited to observed behaviour, a significant amount of effort was spent on analyzing the order of actions in a plan under different configurations. The objective was to generate a search tree that, given human bounds, was considered during the plan generation phase. A human-like utility function then needed to rank discovered plans using an approach that was either rational in the economic sense with expected utility function $exp(t)$ or based on a more human-like evaluation function like $ecoc(x)$. This analysis demonstrated how goals might be grouped based on observed actions. In the tests conducted here, goals were grouped in a reasonable way. For example, visiting a case worker could satisfy multiple goals since a case worker can be responsible for organizing several services for a client.

Finally, it is worth noting that only a forward depth-first search type was utilized and evaluated in this thesis. Other search types like recursive, island-driven, or breadth-first search were not. Recursive search was initially evaluated but was deemed out of scope. These are discussed under future research in Section 8.4.

8.2.6 Bounded Rationality

Bounds represent different aspects of an agent's constraints. While many AI systems acknowledge bounded rationality (BR) and most focus on overcoming related limitations, this thesis explicitly defines and implements each one. This allows BR to be part of the high-fidelity model that can be manipulated to evaluate the types of plans different bound configurations produce. For example, people with cognitive impairments but remarkable memory and patience can be configured with a low cognitive bound ($BR(C)$) but high time ($BR(T)$) and information ($BR(I)$) bounds. The plans BR configurations produce vary greatly, providing clues into impairments by observing the resulting behaviour. Section 5.4.2 specifically focuses on human-centric methods for dealing with such bounds.

8.2.7 Maslow's Hierarchy and Goal Ordering

Maslow's hierarchy (MH) was used as a human-centric way to order and rank goals. This thesis makes the distinction between MH as preferences and as a reflection of reality. An agent's preferences were used during the plan generation phase, but MH was always used during the execution phase to reflect the "true" order of goals. Different cultures may have some unique preferred goal orderings within their population, while different societies may have different social norms that impact what order is used during the execution phase. For example, a BRAMA agent representing a typical individual in an individualistic society may perceive esteem needs as more important than social needs. Similarly, an agent in an altruistic society could be configured to rank self-actualization needs as more important than esteem needs. OSSN was developed in a way that allows for domain-specific mappings between requests made by clients and levels of the hierarchy. The mappings also provide changes in goal rankings based on the agent's motivations and demographics.

8.2.8 Emotional Cycle of Change

As clients' mood state was not captured by data, emotions were a difficult aspect to represent. BRAMA did not rely on *a priori* assignment of events to emotional responses, as per existing work discussed in Section 2.4.4. Rather, emotions were perceived as a motivating or demotivating factor at different points of a plan's execution, controlling an agent's stages of optimism and pessimism about their plan. The $ecoc(x)$ function was used to control how expected utility changed for different stages of an emotional agent. A limitation of the current implementation of BRAMA is the assumption that at the beginning of plan generation and execution phases, each plan starts at the first ECOC stage, uninformed optimism (UO). The BRAMA agent currently has no way of remembering which phase it is in before starting to plan, replan, or execute a plan. This is a limitation of the models in that they do not learn new information. What ECOC provides is an approximation of how people adjust to the execution of a plan, whether optimistically or pessimistically. BRAMA also provides a working example of human-centric replanning and goal reranking based on changing emotional states. Future models would benefit from a more robust stage initialization process.

Triggers for replanning provided the model with a customizable property for the resilience of an agent. The *ecoc-th* threshold allows an agent to follow a resolute or myopic strategy during plan execution. It would be possible to overcome the limitation of starting each plan at the UO stage by updating *ecoc-th* to change an agent's strategies between resolute and myopic. A practical example of this might be someone who began the Housing First program after previously having been in a program that prepared them for being housed. This scenario would start the agent with a lower *ecoc-th* threshold, indicating higher resilience and a resolute strategy. This type of change would not have been reflected in the current version of BRAMA.

For ECOC to sufficiently capture an agent's movement through ECOC stages, there is a minimum number of goals that must exist. Otherwise, not all stages are represented. For example, having one goal results in a utility of 1.0. Having two goals at the same MH level results in 0.3 and 1.0 for actions satisfying the two goals. Having three goals at the same MH level gives the utilities 0.7, 0.5, and 1.0. Each reflects the $ecoc(x)$ function in different ways. With a small number of goals at each level, an agent's movement between stages is much more rigid than in real life, which is more fluid.

8.3 Contributions

Early on in the investigation into social service evaluation, it became apparent that the least represented part of systems in use today were the clients themselves. A key difficulty of representing clients was their seemingly "irrational" behaviour in response to well-planned and structured intervention programs. Since then, the focus of this thesis has been to explain this "irrationality" in a way that can be understood through existing models of human behaviour by creating a high-fidelity client emulation model. Each contribution brings the AI community closer to a complete simulation of social service clients and a more realistic presentation of the services themselves.

Explicit Bounded Rationality The first contribution is the explicit definition and implementation of bounded rationality in an AI planning algorithm. Any AI system with finite resources is bounded by at least one of the bounds. If a domain is small enough or understood well enough, it may be possible to find all possible solutions. However, most problems are not sufficiently well understood, hence most systems must overcome bounds through efficiency improvements. BRAMA is different in that it recognizes client limitations and provides explicit definitions and implementations of these limitations to be used by a rational reasoner. The bounds are not deficiencies of the system but a requirement for a configurable, high-fidelity model. Unlike other systems, the focus is not making human-like reasoning more efficient but making the reasoner itself more human-like. A key step towards this was the recognition that the observer is not omniscient but bounded like its subjects.

Reasoning with Human-Centric Goals The second contribution is the grounding of AI planning goals in basic human needs defined by Maslow's hierarchy. A set of measures were defined to incorporate the hierarchy for goal ordering and utility calculation. A definition of basic needs in the social service domain provided steps for mapping explicit goals expressed by clients to basic needs. This provides an explicit goal ordering. The BRAMA utility function enforces the order by penalizing plans that satisfy goals out of that order.

Three different goal rankings were identified and incorporated in BRAMA. The agent's preferred goal ranking captures an individual's unique and subjective preferences, without justification or explanation. Relying on the Calgary Homeless Foundation (CHF) data for clients' preferred ranking provides much needed empirical grounding of the agent's ranking and the model's validation process. Maslow's ranking provides an objective order of goals, one that could be representative of reality. The mapping of requests made by CHF clients to each MH level is a non-trivial process. Domain-specific mappings were created to correctly associate a client's request with an appropriate level. Finally, the practical ranking represents the order goals are actually satisfied in once a client moves through the social service system. It takes into account constraints placed on the service providers that impact the scheduling of services and management of resources.

Emotional Cycle of Change The third contribution is the incorporation of the emotional cycle of change. Using a continuous function rather than predefined direct associations between events and emotional responses makes it possible to capture dynamic emotional behaviour over an extended period of time. This was required since *a priori* emotional behaviour models are not available for individuals living outside of social norms, like the homeless population.

Human-Centric Replanning The fourth contribution is the replanning algorithm, which extends a bounded-agent model to include emotion-based thresholds. The thresholds add to the fidelity of the model. They provide another configurable measure for defining how resilient an agent is to the stresses of executing a plan. The replanning process also controls the reranking of goals during plan execution.

Emulating Irrational Behaviour The fifth contribution is the emulation of seemingly irrational behaviour with the use of a rational reasoner. Although somewhat paradoxical, the driving premise of this thesis has been that social service clients, like all individuals, are rational, but are bounded by different limitations and have different beliefs and desires than the general population. The STRIPS-BR reasoner is an extension to traditional STRIPS [83]. STRIPS-BR incorporates all human-centric contributions described above. STRIPS-BR also provides an algorithm to emulate "irrational" behaviour grounded in dynamic subjective and sequential decision theories. Limitations of applying decision theory to human-centric behaviour were reviewed in Section 5.3. Many of the limitations lie in the assumptions axioms make about either the omniscience of the observer or the independence of individual choices. The theoretical analysis of these axioms is presented. The analysis first focuses on the importance of observable behaviour over assumptions about the internal processing of an individual's decision making. Second, the analysis highlights how subjective goal and action utility is calculated from a bounded observer's perspective.

Ontology of Social Service Needs The sixth contribution is the representation of the social service domain from the perspective of a service client. The ontology of social service needs (OSSN) provides a vocabulary for capturing client needs, and linking them to specific services. Until now, all such ontologies captured the processes and metrics of service providers, not their recipients. Any constraints presented were those of the service provider, such as scheduling and inventory constraints.

Instead, OSSN captures basic needs, explicit goals, goal ranking, and constraints faced by clients. The service providers are represented through the resources they provide and services they offer that relieve client constraints. The multi-MH representation employed by OSSN allows different stakeholders to be captured, with unique and dynamic changes between goals, constraints, and resources. The basic goal semantics provide a starting point for categorizing goals and their relations to basic needs and other goals. The categorization is then used to define an individual's needs and motivation within OSSN.

As a final step, the OSSN guides the process for mapping client needs to services and process of an existing service provider. Once mapped, BRAMA can provide client emulation, making it possible for any compatible system to measure its performance with a focus on client outcomes. The performance is based on a client's interaction with specific services over an extended period of time. Based on this performance analysis, OSSN can help identify what services may be missing, and how well specific homeless communities are being supported.

8.4 Future Research

The research presented in this thesis addresses some of the fundamental limitations towards meeting the original objectives of emulating "irrational" behaviour and evaluating social service intervention programs. More work is needed towards improving methods developed here, extending BRAMA to new domains, and answering several new questions that arose as a result of this research.

Independence of ECOC and Maslow's Hierarchy The work presented here assumed that emotional state and goals were initially independent, linked only by jointly contributing to plan utility. No special order of goals was provided for emotional states. Also, no special emotions were assigned to specific goals or MH levels. This may not be the case in real life, as one can imagine a scenario where individuals have an emotional attachment to certain goals. For example, social connections people make are highly emotional, and would fall under the social goal category. Similar arguments can be made about other levels.

Questionnaire Development One of the limitations encountered early on was the limited data that was available. Aside from privacy issues and access to data, certain fields were not being regularly collected. Every client is different, and demographics are not a sufficient indicator of success or failure in a program. Client life experiences and response to the program varies greatly. Analysis of data requirements for program evaluation metrics based on client needs and progress needs to be performed. More data about factors impacting client decision making is required, including their emotional state and available resources in and outside of the service system.

Constraint Analysis A deeper understanding of the constraints faced by clients is needed. This would extend OSSN and enhance the fidelity of the BRAMA model. It would also create a more realistic representation of service providers by extending the action schema. This includes the limitations faced by service providers as well as study administrators in the social service domain [76]. The constraints captured in OSSN are a summary of factors that prevent clients from satisfying their goals. A more granular representation is needed.

Dynamic and Evolving Agent Model Certain components of BRAMA remained static. The agent reasoning would benefit from learning capabilities that mimics that of real service clients during the execution phase. More dynamic adjustments to thresholds during search would greatly improve the model. The current model assumes *ecoc-th* and *action-th* do not change; as an agent progresses however, its thresholds may change. This would reflect changes in resilience as the agent gets more or less skilled or adopts new strategies during the plan execution phase. Currently, a BRAMA agent emulates adjusting to plan execution through the nonlinear ECOC utility function. This is an approximation of the real changes in behaviour that occur while clients participate in an intervention program, and a stark contrast to the monotonically increasing utility functions used in economic theories of rational agents.

Also, the information bound $BR(I)$ can be made dynamic if the agent learns to perform new actions that are added to its action schema. This functionality could be used to evaluate how much information an agent retains or learns during plan creation and execution phases. In addition to adding and deleting states, such "teaching" actions could add and delete actions in the action schema. Currently, a BRAMA agent can learn new information if it is provided as an add-proposition of an action. Learning new actions is not supported. During the planning phase, expected utility is used to rank goals and actions. During the execution phase, BRAMA assumes actions performed with a 100% success rate. The simulation can be extended with probabilistic action execution that captures the rate with which providers are successful in delivering services to clients.

The approach to goal ranking and replanning presented here incorporates ideas from a number of fields that aim to reproduce human-like behaviour. Additional models of goal reasoning can be incorporated provided they aim to emulate rather than optimize human-like reasoning. For example, goal preference can be learned over time. It is possible that over time an agent adjusts its preferences to match the practical order of outcomes, where $rank(A, s_i) = rank(x, s_i)$ for all goals $s_i \in G\text{-}BR$ given some previously executed plan P^x. How that comes about in homeless clients requires further research. Also, BRAMA can benefit from hierarchical goal and task networks [225], provided they can be grounded in a human-centric representation like Maslow's [160] framework.

Alternative Search Types The search used by STRIPS-BR is a forward depth-first search, however there is much evidence to suggest human-centric planning uses different search strategies. For example, working backwards from a problem is a common technique, and may be emulated by relying on recursive search. This was investigated initially but was deemed outside the scope of this thesis. An island-driven search was not investigated fully, but some observed similarities to the search algorithm deployed by BRAMA agents are worth mentioning. An island search identifies required intermediate states towards reaching a goal state, guiding the search process. During the replanning phase, the final state before replanning begins is an example of such an "island" state. More analysis is needed to incorporate this into the search. Also, with $BR(C) = 1$, STRIPS-BR is essentially a breadth-first search that evaluates all states one level down in the search tree before selecting a state and continuing the search process. In this sense, the STRIPS-BR planner deploys what can be described as a multi-level breadth-first search controlled by $BR(C)$. The conditions for replanning and choosing the next goals and plan can be viewed as a heuristic for selecting potential paths to pursue. A dynamic process for evaluating starting ECOC stages and replanning thresholds could control such a heuristic.

An island-driven search could be used to simulate human-like planning in a way that considers abstract planning [72]. By using actions that omit preconditions, a high-level abstract plan is created to reduce the exponential growth of goals to possibly within the agent's cognitive limit. The island-driven search generates several states that must be in the search space. Each "island" is made up of states s_i for actions $a_m \in AS\text{-}BR$ where $s_i \in G\text{-}BR_t \cup POST_m$ at time step t. Once the actions are added to the abstract plan, their add-propositions are added to $G\text{-}BR_t^S$ indicating they are now satisfied goal states. At some later stage, correct actions are used and their true preconditions added to $G\text{-}BR_t$ as unsatisfied goal states. A new search is then performed that satisfies the newly added goal states.

Smart Cities Social services is one of many responsibilities managed by different levels and branches of government. In that context, social services is a subsystem that interacts with many other such systems within a city. The approach developed here would benefit the evaluation of policy impacting such systems, especially at the municipal level. Studies into human behaviour within this type of system-of-systems framework would benefit other services that impact or are impacted by the behaviour of individual citizens, including transportation, healthcare, hydro, and power consumption. For example, adjusting emergency services would benefit from knowing the potential stress on resources that higher patient loads would have on individual practitioners and existing patients. Smart homes may detect emotional patterns in individuals and organize appliances and home utilities not just around the occupant's schedules but also around their changes in mood throughout the day.

Intelligence Augmentation There is a growing trend towards the automation of work-related responsibilities that demand cognitive rather than physical labour, such as the work of accountants, analysts, and some managerial work that could also be automated. The area of intelligence augmentation is concerned with creating decision support systems for assisting humans with micro-decisions that require some cognitive ability and human intuition, and relies on three research areas. AI research has traditionally led the way in developing such decision support systems and automating large decision tasks. The field of human-computer interaction research has focused on how best to incorporate such systems with minimal negative impact on its users. Finally, organizational psychology research focuses on how best to incorporate such systems at the organizational level.

Much of the work that went into the development of BRAMA agents is based on research initially developed in the organizational psychology field. Hence, much of BRAMA can be applied to domains this field traditionally applies to. For example, organizational psychology has developed many theories that rely on traditional exchange of monetary goods for services provided by employees. As new economies develop, the incentives of workers change. Understanding those incentives is an interesting research area that requires a deeper understanding of employee goals, motivations, and how employees view themselves as "global citizens."

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Appendix A

Calgary Homeless Foundation and Data Analysis

This appendix provides a description and evaluation of the CHF-HF data, questionnaires, and collected attributes. The evaluation is based on the analysis performed by [257], where analysis was performed on the At Home/Chez Soi (AH-CS) Housing First intervention program. A full description of the program can be found at [95]. The analysis presented in this appendix applies similar analysis to the Housing First program administered by the Calgary Homeless Foundation (CHF-HF).

A.1 Participation Selection

Defining characteristics of clients receiving Housing First support is that they are currently or at risk of experiencing homelessness. A key factor in successfully implementing the program is that client needs are matched to services available. Calgary has implemented an integrated system approach ensuring multiple programs form a "system of care" that centres around client needs.

Point of entry can be any service. Intake forms is filled out by the point-of-entry organization. Each agency must work with people experiencing a variety of housing needs. People experiencing chronic homelessness or sleeping rough are prioritized. Individual programs are tailored to the needs of vulnerable subpopulations, including youth, aboriginal, and women. For a housing program to work, there must a be partnership between the agencies and landlords and building managers.

A.2 CHF-HF Questionnaires (HF Assessment Forms)

HF Assessment questionnaires administered by Calgary Homeless Foundation during the Housing First program. Data collected using the following three forms was used in the CHF-HF dataset.

1. Once housing is found, the client is relocated to the new location and given the move-in assessment form: "Move-in-Assessment (v 7.27.2015)."
2. The follow-up assessment questionnaire is administered every 3 months: "General-HS-HF-3-60-Month-Follow-Up-Interview (v 10.16.2015)."
3. When a client exits the program, successfully or otherwise, the exit assessment form is administered: "Exit-Assessment (v 7.27.2015)."

HOUSING FIRST MOVE-IN ASSESSMENT

Calgary HMIS

This form is to be completed within the month of a client's date of move-in.

FOIP NOTIFICATION

This personal information is being collected under the authority of Section 33(c) of the Freedom of Information and Protection of Privacy ACT (the `FOIP`) and/or in accordance with any applicable agreements in place. All personal information collected during the registration process, during the course of the client`s stay, and for participation in any programs will be used to provide services and ensure a safe and secure environment for all our clients. It will be treated in accordance with the privacy provision of Part 2 of the FOIP. Limited information may also be provided to the Minister of Human Services for the purpose of carrying out programs, activities or policies under his administration (e.g. research, statistical analysis) or for receiving provincial and/or federal funding. Do you have any questions or concerns?

The FOIP notification has been read and discussed with the client? ☐ Yes ☐No

PROGRAM-LEVEL INFORMATION

Program name:

Case worker name: | Case worker phone number:

Date of Intake Assessment (mm/dd/yyyy):

Client referred by:

☐ CAA – High Acuity ☐ CAA – Mid Acuity ☐ CAA - Families ☐ CAA - Youth

☐ Self ☐ Don't know ☐ Declined to answer ☐ Not applicable ☐ Other

If "Other" referral source, please specify:

Date of move in (mm/dd/yyyy): | Date lease signed (mm/dd/yyyy):

BASIC INFORMATION

Last name:	First name:	Middle name:	Prefix:
			Suffix:

Also known as (A.K.A.)/ Nickname(s):	Date of birth:	Age:

What is your gender?

☐ Female ☐ Male ☐ Transgender ☐ Transsexual ☐ Don't know ☐ Declined to answer

What is the postal code of your last **permanent** address?

________________________ ☐ Don't know ☐ Declined to answer

What is the neighborhood of your last **permanent** address?

________________________ ☐ Don't know ☐ Declined to answer

IDENTIFICATION

Are you able to produce the following forms of identification? (Check all that apply)

☐ Birth Certificate ☐ Driver's License ☐ Government issued ID ☐ Health card ☐ SIN ☐ No ID ☐ Other ___________________

☐ Don't know ☐ Declined to answer

LANGUAGE

What is your primary language?

☐ English ☐ French ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

VETERAN STATUS

Have you ever served in the Canadian Forces?

☐ Yes ☐No ☐ Don't know ☐ Declined to answer

CITIZENSHIP AND MIGRANT STATUS

What is your current citizenship and immigration status?

☐ Canadian citizen ☐ Permanent resident (Landed immigrant) ☐ Refugee - Permanent resident ☐ Refugee - Claimant
☐ Temporary Foreign Worker ☐ International student ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

What is your current migrant status?

☐ New to province (within 3 months) ☐ Recent immigrant (within 3 years) ☐ Recent immigrant and new to province ☐ Don't know
☐ Declined to answer ☐ Not applicable

ETHNICITY

What is your ethnicity?

☐ Caucasian ☐ Aboriginal ☐ Chinese ☐ South Asian ☐ African/Caribbean ☐ Filipino ☐ Latin American ☐ Southeast Asian
☐ Arab ☐ West Asian ☐ Korean ☐ Japanese ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

If Aboriginal ethnicity, which group do you belong to?

☐ First Nations (Status) ☐ First Nations (Non-Status) ☐ Métis ☐ Inuit ☐ Don't know ☐ Declined to answer ☐ Not applicable

FAMILY INFORMATION

Which of the following best describes your current family situation?

☐ Single ☐ Couple ☐ Single parent family ☐ Head of two-parent family ☐ Other parent in two-parent family
☐ Other ☐ Don't know ☐ Declined to answer

Are you pregnant? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

How many dependents (under 18) do you have? (Only include those also enrolled in the program)

Are Child Protective Services involved with you or your family? ☐ Yes ☐No ☐ Don't know ☐ Declined to answer

Have you been exposed to/are you currently fleeing from family violence?

☐ Yes ☐No ☐ Don't know ☐ Declined to answer

HOMELESSNESS HISTORY (PLEASE CHOOSE CHRONIC OR EPISODIC FOR THE FOLLOWING QUESTIONS)

Are you chronically homeless? (Def'n: *Client has either been continuously homeless for a year or more, or has had at least 4 episodes of homelessness in the past 3 years. Person must have been sleeping in a place not meant for human habitation and/or in an emergency homeless shelter*)
☐ Yes ☐ No

If chronic, how many **times** have you lived in shelters/outside in your lifetime?

If chronic, how many **years** have you been homeless?

☐ 1 year ☐ 2 years ☐ 3 years ☐ 4 Years ☐ 5 years or more ☐ Don't know ☐Declined to answer

Are you episodically homeless? (Def'n: Homeless for less than a year and has fewer than 4 episodes of homelessness in the past three years)
☐ Yes ☐ No

If episodic, how many times have you lived in shelters/outside over the last year?

If episodic, how many **months** have you been homeless?

☐ Less than 1 month ☐ 1-3 months ☐ 4-6 months ☐ 7–12 months ☐ Don't know ☐Declined to answer

PERSONAL HISTORY

Have you recently (past 12 months) been released from a correctional facility?	☐ Yes	☐No	☐ Don't know	☐ Declined to answer
Have you recently (past 12 months) been released from a mental health facility?	☐ Yes	☐No	☐ Don't know	☐ Declined to answer
Have you recently (past 12 months) been released from a residential addiction facility?	☐ Yes	☐No	☐ Don't know	☐ Declined to answer
Have you recently (past 12 months) been released from a health facility?	☐ Yes	☐No	☐ Don't know	☐ Declined to answer
Have you recently (past 12 months) been evicted from a residence?	☐ Yes	☐No	☐ Don't know	☐ Declined to answer

Have you ever been in foster care? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

Updated: 07/27/2015

HOUSING NEEDS

Are you absolutely (*i.e. emergency shelter or street*) or relatively (*i.e. living in spaces that don't meet health and safety standards*) homeless?

☐ Absolute ☐ Relative

What was your primary residence prior to program entry?

☐ Outside (rough sleeping, camping, vehicle) ☐ Dwelling unfit for human habitation ☐ Emergency shelter ☐ Addictions treatment facility
☐ Staying with family or friends (couch surfing) ☐ Correctional facility ☐ Hospital/medical facility ☐ Child Intervention Services placement
☐Hotel/motel ☐ Transitional housing ☐ Long-term housing with supports ☐Renting – Subsidized ☐Renting – Unsubsidized
☐ Own home ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

INCOME

What are your current sources of **monthly** income (before tax)? (Check all that apply and indicate amount)

☐ Aboriginal Funding $________
☐ Alberta Works/Income Support $________
☐ Assured Income for the Severely Handicapped (AISH) $________
☐ Binning/Recycling/Bottle Picking $________
☐ Canada Pension Plan Benefits $________
☐Canada Pension Plan Disability Benefits $________
☐ Child Support/Alimony $________
☐ Child Tax Credit $________
☐ Employment Insurance (EI) $________
☐ Full-time Employment $________
☐ Guaranteed Income Supplement or Survivor's Allowance $________
☐ Housing Supplements $________
☐ Long-term Disability (private) $________
☐ Old Age Security Pension (OAS) $________
☐ Other Tax Credits $________
☐ Panhandling $________
☐ Part-time Employment $________
☐ Retirement pensions, superannuation & annuities $________
☐ Self Employed $________
☐ Student Funding $________
☐ War Veterans Allowance/Veterans Benefits $________
☐ Workers' Compensation Benefit $________
☐No Income
☐ Other _______________ $________
☐Don't know
☐ Declined to answer

EMPLOYMENT TRAINING AND EDUCATION

Are you currently employed?

☐ Yes - Full-time ☐ Yes – Part-time ☐ Yes - Casual/Contract ☐ Yes - Seasonal ☐ No - Unable to work ☐ No
☐ Don't know ☐ Declined to answer

If unemployed, for how many months have you been unemployed?

☐ 1 month or less ☐ 2 months ☐ 3 months ☐ 4 months ☐ 5 months ☐ 6-12 months ☐1-3 years ☐More than 3 years
☐ Don't know ☐ Declined to answer ☐ Not applicable

What is your current employability status? ☐ Employable ☐ Not employable at this time ☐ Don't know ☐ Declined to answer

Are you currently attending employment related training? ☐ Yes - Full-time ☐ Yes – Part-time ☐ No ☐ Don't know ☐ Declined to answer

Are you currently attending further education classes? ☐ Yes - Full-time ☐ Yes – Part-time ☐ No ☐ Don't know ☐ Declined to answer

What is the highest level of education you have attained?

☐ Less than junior high ☐ Completed junior high ☐ Some high school ☐ Completed high school ☐ Some post-secondary (college/technical)
☐ Completed post-secondary (college/technical) ☐ Some post-secondary (university) ☐ Completed post-secondary (university)
☐ Don't know ☐ Declined to answer

BASIC NEEDS ASSISTANCE

What basic needs assistance do you currently require?

☐ Child care ☐ Clothing ☐ Debt reduction ☐ Disability support ☐ Employment training ☐ Food ☐ Furniture
☐ Housing supplement ☐ Identification ☐ Medication ☐ Rent arrears ☐ Rent shortfall/subsidy ☐ Security deposit
☐ Tenant insurance support ☐ Transportation ☐ Utility arrears ☐ None ☐ Other ____________________
☐ Don't know ☐ Declined to answer

HEALTH INFORMATION
Do you have an ongoing mental health condition? ☐ Yes - Treated ☐ Yes- Untreated ☐ Yes- Both treated and untreated ☐ No ☐ Don't know ☐ Declined to answer
Do you have an ongoing physical health condition? ☐ Yes - Treated ☐ Yes- Untreated ☐ Yes- Both treated and untreated ☐ No ☐ Don't know ☐ Declined to answer
Do you have an addictions/substance abuse issue? ☐ Yes - Treated ☐ Yes- Untreated ☐ Yes- Both treated and untreated ☐ No ☐ Don't know ☐ Declined to answer
Do you have Fetal Alcohol Spectrum Disorder (FASD)? ☐ Yes – Client suspected ☐ Yes- Diagnosed ☐ No ☐ Don't know ☐ Declined to answer
Do you require specialized housing accommodations due to a disabling condition? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer If yes, please specify: ______________________
Have you had any involvement with the health system in the past 12 months while you were homeless? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer
If any, how many **days** in total have you spent hospitalized in the past 12 months?
If any, how many **times** have you been hospitalized in the past 12 months?
If any, how many **times** have you utilized Emergency Medical Service (EMS) in the past 12 months?
If any, how many **times** have you been to a hospital emergency room in the past 12 months?
JUSTICE AND LEGAL INFORMATION
Have you had any involvement with the police or the legal system in the past 12 months while you were homeless? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer
If any, how many **days** in total have you spent in jail in the past 12 months?
If any, how many **times** have you been to jail in the past 12 months?
If any, how many **times** have you had interactions with the police in the past 12 months?
If any, how many court appearances have you had in the past 12 months?

NOTES:

HOUSING FIRST FOLLOW-UP ASSESSMENT (3-60 MONTH)

Calgary HMIS

Once a client has secured a move-in date, this form is to be completed every 3 months until their program exit or until they have reached 5 years (60 months) in a program.

Is follow-up required?

☐ Yes (please fill out interview questions below)

☐ Yes, Client is still in program but is missing/unavailable (known answers to be filled in only)

If no, please proceed to exit interview.

PROGRAM-LEVEL INFORMATION

Date of ____ Month Follow-up Assessment (mm/dd/yyyy):

Program name:	Program entry date:
Case worker name:	Case worker phone number:

BASIC INFORMATION

Last name:	First name:	Middle name:	Prefix:
			Suffix:

Also known as (A.K.A.)/ Nickname(s):	Date of birth:	Age:

What is your gender?

☐ Female ☐ Male ☐ Transgender ☐ Transsexual ☐ Don't know ☐ Declined to answer

LANGUAGE

What is your primary language?

☐ English ☐ French ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

VETERAN STATUS

Have you ever served in the Canadian Forces?

☐ Yes ☐No ☐ Don't know ☐ Declined to answer

CITIZENSHIP & MIGRANT STATUS

What is your current citizenship and immigration status?

☐ Canadian citizen ☐ Permanent resident (Landed immigrant) ☐ Refugee - Permanent resident ☐ Refugee - Claimant ☐ Temporary Foreign Worker ☐ International student ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

What is your current migrant status?

☐ New to province (within 3 months) ☐ Recent immigrant (within 3 years) ☐ Recent immigrant and new to province ☐ Don't know ☐ Declined to answer ☐ Not applicable

ETHNICITY

What is your ethnicity?

☐ Caucasian ☐ Aboriginal ☐ Chinese ☐ South Asian ☐ African/Caribbean ☐ Filipino ☐ Latin American ☐ Southeast Asian ☐ Arab ☐ West Asian ☐ Korean ☐ Japanese ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

If Aboriginal ethnicity, which group do you belong to?

☐ First Nations (Status) ☐ First Nations (Non Status) ☐ Métis ☐ Inuit ☐ Don't know ☐ Declined to answer ☐ Not applicable

HOUSING HISTORY

Are you currently in stable housing? (If client is waiting to be rehoused, select 'No')

☐ Yes ☐No ☐ Don't know ☐ Declined to answer

Have you achieved permanent housing throughout the past 3 months?

☐ Yes ☐No ☐ Don't know ☐ Declined to answer

Were you rehoused within the last 3 months? ☐ Yes ☐No ☐ Don't know ☐ Declined to answer

FAMILY INFORMATION

Has your family situation changed since the last follow-up was completed? ☐ Yes ☐No ☐ Don't know ☐ Declined to answer

Which of the following best describes your current family situation?

☐ Single ☐ Couple ☐ Single parent family ☐ Head of two-parent family ☐ Other parent in two-parent family

☐ Don't know ☐ Declined to answer

Are you pregnant? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

How many dependents (under 18) do you have? (only include those also enrolled in the program) ________

BASIC NEEDS ASSISTANCE

What basic needs assistance have you received during the last 3 months?

☐ Child care ☐ Clothing ☐ Debt reduction ☐ Disability support ☐ Further education ☐ Employment training ☐ Food

☐ Furniture ☐ Housing supplement ☐ Identification ☐ Medication ☐ Rent arrears ☐ Rent shortfall/subsidy ☐ Security deposit

☐ Tenant insurance support ☐ Transportation ☐ Utility arrears ☐ None ☐ Other ___________________

☐ Don't know ☐ Declined to answer

SERVICE REFERRALS

What service referrals have you received during the last 3 months?

☐ Aboriginal agencies ☐ Addictions service ☐ Child support service ☐ Counseling ☐ Financial service

☐ Health service (non-hospital) ☐ Hospital ☐ Immigrant serving agencies ☐ Legal service ☐ Police service ☐ None

☐ Other ___________________ ☐ Don't know ☐ Declined to answer

CASE WORKER CONTACT

How often does your case worker visit or contact you each month?

☐ 1-10 times ☐ 11-20 times ☐ 21-30 times ☐ 31 times or more ☐ Don't know ☐ Declined to answer

EMPLOYMENT TRAINING AND EDUCATION

Have you gained paid employment within the past 3 months?

☐ Yes - Full-time ☐ Yes – Part-time ☐ Yes - Casual/Contract ☐ Yes - Seasonal ☐ No - Unable to work ☐ No
☐ Don't know ☐ Declined to answer

Are you currently attending employment related training? ☐ Yes - Full-time ☐ Yes – Part-time ☐ No ☐ Don't know ☐ Declined to answer

Have you completed an employment related training program within the past 3 months? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

Are you currently attending further education classes? ☐ Yes - Full-time ☐ Yes – Part-time ☐ No ☐ Don't know ☐ Declined to answer

INCOME

What are your current sources of **monthly** income (before tax)? (Check all that apply and indicate amount)

☐ Aboriginal Funding $________

☐ Alberta Works/Income Support $________

☐ Assured Income for the Severely Handicapped (AISH) $________

☐ Binning/Recycling/Bottle Picking $________

☐ Canada Pension Plan Benefits $________

☐Canada Pension Plan Disability Benefits $________

☐ Child Support/Alimony $________

☐ Child Tax Credit $________

☐ Employment Insurance (EI) $________

☐ Full-time Employment $________

☐ Guaranteed Income Supplement or Survivor's Allowance $________

☐ Housing Supplements $________

☐ Long-term Disability (private) $________

☐ Old Age Security Pension (OAS) $________

☐ Other Tax Credits $________

☐ Panhandling $________

☐ Part-time Employment $________

☐ Retirement pensions, superannuation & annuities $________

☐ Self Employed $________

☐ Student Funding $________

☐ War Veterans Allowance/Veterans Benefits $________

☐ Workers' Compensation Benefit $________

☐No Income

☐ Other _______________ $________

☐Don't know

☐ Declined to answer

SOCIAL PARTICIPATION

Have you engaged in volunteer work during the past 3 months?

☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

Have you engaged in recreational or cultural programs/services during the past 3 months?

☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

Have you experienced positive changes in your social participation during the past 3 months?

☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

HEALTH INFORMATION

Have you been diagnosed with any of the following in the last 3 months? (Check all that apply)

☐ Physical health issues ☐ Mental health issues ☐ None ☐ Don't know ☐ Declined to answer

Do you have an ongoing mental health condition? ☐ Yes - Treated ☐ Yes- Untreated ☐ Yes- Both treated and untreated ☐ No ☐ Don't know ☐ Declined to answer

Do you have an ongoing physical health condition? ☐ Yes - Treated ☐ Yes- Untreated ☐ Yes- Both treated and untreated ☐ No ☐ Don't know ☐ Declined to answer

Do you have an addictions/substance abuse issue? ☐ Yes - Treated ☐ Yes- Untreated ☐ Yes- Both treated and untreated ☐ No ☐ Don't know ☐ Declined to answer

Do you have Fetal Alcohol Spectrum Disorder (FASD)? ☐ Yes – Client suspected ☐ Yes- Diagnosed ☐ No ☐ Don't know ☐ Declined to answer

Have you had any involvement with the health system in the past 3 months?

☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

If any, how many **days** in total have you spent hospitalized in the past 3 months? ________

If any, how many **times** have you been hospitalized in the past 3 months? ________

If any, how many **times** have you utilized Emergency Medical Service (EMS) in the past 3 months? ________

If any, how many **times** have you been to a hospital emergency room in the past 3 months? ________

JUSTICE AND LEGAL INFORMATION

Have you had any involvement with the police or the legal system in the past 3 months?

☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

If any, how many **days** in total have you spent in jail in the past 3 months? ________

If any, how many **times** have been to jail in the past 3 months? ________

If any, how many **times** have you had interactions with the police in the past 3 months? ________

If any, how many court appearances have you had in the past 3 months? ________

DISCHARGE PLANNING

IT IS ONLY NECESSARY TO COMPLETE THE FOLLOWING IF CLIENT IS COMPLETING A 9 OR 12 MONTH FOLLOW UP

What assistance do you require for discharge planning? (Check all that apply)

☐ Support services required – complete question below ☐ No support services required for discharge planning ☐ No support services required as client is not being discharged ☐ Don't know ☐ Declined to answer

If support services are required, what services do you need? (Check all that apply)

☐ Mental health ☐ Addictions/Substance abuse issues ☐ Physical health ☐ Household maintenance ☐ Ongoing rental supplements/support ☐ Other ___________________ ☐ Don't know ☐ Declined to answer

NOTES:

HOUSING FIRST EXIT ASSESSMENT

Calgary HMIS

This form is to be completed upon a client's exit from a program.

PROGRAM-LEVEL INFORMATION

Date of Exit Interview (mm/dd/yyyy):

Program name:	Program exit date:
Case worker name:	Case worker phone number:

BASIC INFORMATION

Last name:	First name:	Middle name:	Prefix: Suffix:

Also known as (A.K.A.)/ Nickname(s):	Date of birth:	Age:

What is your gender?

☐ Female ☐ Male ☐ Transgender ☐ Transsexual ☐ Don't know ☐ Declined to answer

EXIT INFORMATION *(to be input into Entry/Exit tab in the HMIS)*

Why is the client leaving the program?

☐ Completed program ☐ Criminal activity/violence ☐ Death ☐ Disagreement with rules/persons ☐ Left for housing opportunity before completing program ☐ Needs could not be met ☐ Non-compliance with program ☐ Non-payment of rent ☐ Reached maximum time allowed ☐ Referred to another program ☐ Transferred to HS HF program (new program to continue assessments) ☐ Unknown/disappeared ☐ Other ____________________

What is the client's destination?

☐ Outside (rough sleeping, camping, vehicle) ☐ Dwelling unfit for human habitation ☐ Emergency shelter ☐ Addictions treatment facility ☐ Staying with family or friends (couch surfing) ☐ Correctional facility ☐ Hospital/medical facility ☐ Child Intervention Services placement ☐Hotel/motel ☐ Transitional housing ☐ Long-term housing with supports ☐Renting – Subsidized ☐Renting – Unsubsidized ☐ Family home ☐ Own home ☐ Other ________________ ☐ Declined to answer ☐ Caseworker doesn't know (Client unknown/disappeared)

Can Exit Interview be completed by client? ☐ **Yes (please fill out interview questions below)**
☐ **No (known answers below to be filled in only)**

LANGUAGE

What is your primary language?

☐ English ☐ French ☐ Other __________________ ☐ Don't know ☐ Declined to answer

VETERAN STATUS

Have you ever served in the Canadian Forces?

☐ Yes ☐No ☐ Don't know ☐ Declined to answer

CITIZENSHIP & MIGRANT STATUS

What is your current citizenship and immigration status?

☐ Canadian citizen ☐ Permanent resident (Landed immigrant) ☐ Refugee - Permanent resident ☐ Refugee - Claimant ☐ Temporary Foreign Worker ☐ International student ☐ Other __________________ ☐ Don't know ☐ Declined to answer

What is your current migrant status?

☐ New to province (within 3 months) ☐ Recent immigrant (within 3 years) ☐ Recent immigrant and new to province ☐ Don't know ☐ Declined to answer ☐ Not applicable

ETHNICITY

What is your ethnicity?

☐ Caucasian ☐ Aboriginal ☐ Chinese ☐ South Asian ☐ African/Caribbean ☐ Filipino ☐ Latin American ☐ Southeast Asian ☐ Arab ☐ West Asian ☐ Korean ☐ Japanese ☐ Other __________________ ☐ Don't know ☐ Declined to answer

If Aboriginal ethnicity, which group do you belong to?

☐ First Nations (Status) ☐ First Nations (Non Status) ☐ Métis ☐ Inuit ☐ Don't know ☐ Declined to answer ☐ Not applicable

Updated: 7/27/2015

FAMILY INFORMATION

Has your family situation changed since the last follow-up was completed? ☐ Yes ☐No ☐ Don't know ☐ Declined to answer

Which of the following best describes your current family situation?

☐ Single ☐ Couple ☐ Single parent family ☐ Head of two parent family ☐ Other parent of two parent family ☐ Other
☐ Don't know ☐ Declined to answer

Are you pregnant? ☐ Yes ☐ No ☐ Don't know ☐ Declined to answer

How many dependents (under 18) do you have? (only include those also enrolled in the program)

EMPLOYMENT TRAINING

Have you completed an employment related training program within the past 3 months? ☐ Yes - Full-time ☐ Yes – Part-time ☐ No ☐ Don't know ☐ Declined to answer

INCOME

What are your current sources of **monthly** income (before tax)? (Check all that apply and indicate amount)

☐ Aboriginal Funding $________
☐ Alberta Works/Income Support $________
☐ Assured Income for the Severely Handicapped (AISH) $________
☐ Binning/Recycling/Bottle Picking $________
☐ Canada Pension Plan Benefits $________
☐Canada Pension Plan Disability Benefits $________
☐ Child Support/Alimony $________

☐ Child Tax Credit $________
☐ Employment Insurance (EI) $________
☐ Full-time Employment $________
☐ Guaranteed Income Supplement or Survivor's Allowance $________
☐ Housing Supplements $________
☐ Long-term Disability (private) $________
☐ Old Age Security Pension (OAS) $________
☐ Other Tax Credits $________
☐ Panhandling $________
☐ Part-time Employment $________

☐ Retirement pensions, superannuation & annuities $________
☐ Self Employed $________
☐ Student Funding $________
☐ War Veterans Allowance/Veterans Benefits $________
☐ Workers' Compensation Benefit $________
☐No Income
☐ Other ________________ $________
☐Don't know
☐ Declined to answer

HEALTH INFORMATION

Do you have Fetal Alcohol Spectrum Disorder (FASD)? ☐ Yes – Client suspected ☐ Yes- Diagnosed ☐ No
☐ Don't know ☐ Declined to answer

DISCHARGE PLANNING

What ongoing supports do you currently require? (Check all that apply)

☐ Ongoing rental supplement ☐ No further rental support ☐ Mental health support services
☐ Addictions/substance abuse support services ☐ Physical health support services ☐ Household maintenance support services
☐ No further support services ☐ Other ____________________ ☐ Don't know ☐ Declined to answer

CLIENT SATISFACTION

Please rate your overall satisfaction with the program you participated in:

☐ Very satisfied ☐ Satisfied ☐ Neither satisfied nor dissatisfied ☐ Dissatisfied ☐ Very Dissatisfied ☐ Don't know
☐ Declined to answer

Please rate to what extent you agree or disagree with the following statements:

The housing provided to me through the program was appropriate and met my personal needs

☐ Strongly agree ☐ Agree ☐ Neither agree nor disagree ☐ Disagree ☐ Strongly disagree ☐ Don't know ☐ Declined to answer

The support services I received from my case worker were appropriate and met my personal needs to remain housed

☐ Strongly agree ☐ Agree ☐ Neither agree nor disagree ☐ Disagree ☐ Strongly disagree ☐ Don't know ☐ Declined to answer

Through the program, I was provided with assistance to connect with the government services that I required

☐ Strongly agree ☐ Agree ☐ Neither agree nor disagree ☐ Disagree ☐ Strongly disagree ☐ Don't know ☐ Declined to answer

NOTES:

A.3 CHF Participant Characteristic Evaluation

Baseline characteristics of CHF-HF participants and p scores are presented in table A.1. As in [257], the following p values were considered: †$p \leq 0.2$, ††$p \leq 0.1$, $^*p \leq 0.05$, $^{**}p \leq 0.01$, $^{***}p \leq 0.001$.

Table A.1: Baseline characteristics of study participants

Characteristic	Total (N=1,011)	Stable housed (N=205)	People with additional needs (N=806)
Aboriginal, N (%)	235.0 (0.2)	49.0 (0.2)	186.0 (0.2)
Have Addiction - Both Treated and Untreated, N (%)*	149.0 (0.1)	21.0 (0.1)	128.0 (0.2)
Canadian Citizen, N (%)	968.0 (1.0)	198.0 (1.0)	770.0 (1.0)
Served in Canadian Forces? No, N (%)	968.0 (1.0)	197.0 (1.0)	771.0 (1.0)
Age (36 - 50), N (%)	449.0 (0.4)	97.0 (0.5)	352.0 (0.4)
Gender Male, N (%)	507.0 (0.5)	100.0 (0.5)	407.0 (0.5)
Family situation?			
Single, N (%)*	845.0 (0.8)	162.0 (0.8)	683.0 (0.8)
Head of household, N (%)*	166.0 (0.2)	43.0 (0.2)	123.0 (0.2)
No. of dependents (0), mean (SD)*	0.5 (0.4)	0.6 (1.3)	0.4 (0.9)
Not pregnant, N (%)††	977.0 (1.0)	202.0 (1.0)	775.0 (1.0)
What is your primary language?			
English, N (%)**	944.0 (0.9)	201.0 (1.0)	743.0 (0.9)
Other, N (%)**	54.0 (0.1)	3.0 (0.0)	51.0 (0.1)
Highest level of education			
Completed Post Secondary (university), N (%)†	38.0 (0.0)	11.0 (0.1)	27.0 (0.0)
Some High School, N (%)†	311.0 (0.3)	55.0 (0.3)	256.0 (0.3)
Some Post Secondary (college/technical), N (%)†	135.0 (0.1)	33.0 (0.2)	102.0 (0.1)
Employable (is or will be able to work in the short term), N (%)	244.0 (0.2)	55.0 (0.3)	189.0 (0.2)
No Employment Training, N (%)	978.0 (1.0)	200.0 (1.0)	778.0 (1.0)
Employed?			
No, N (%)*	468.0 (0.5)	109.0 (0.5)	359.0 (0.4)
No - Unable to work, N (%)*	433.0 (0.4)	74.0 (0.4)	359.0 (0.4)
If unemployed, for how many months?			
1 month or less, N (%)††	34.0 (0.0)	11.0 (0.1)	23.0 (0.0)
1 to 3 years, N (%)	261.0 (0.3)	55.0 (0.3)	206.0 (0.3)
2 months, N (%)	24.0 (0.0)	3.0 (0.0)	21.0 (0.0)
3 months, N (%)	21.0 (0.0)	6.0 (0.0)	15.0 (0.0)
4 months, N (%)	16.0 (0.0)	3.0 (0.0)	13.0 (0.0)
5 months, N (%)††	16.0 (0.0)	6.0 (0.0)	10.0 (0.0)
6 to 12 months, N (%)†	157.0 (0.2)	38.0 (0.2)	119.0 (0.1)
More than 3 years, N (%)*	330.0 (0.3)	53.0 (0.3)	277.0 (0.3)
Don't know, N (%)**	17.0 (0.0)	8.0 (0.0)	9.0 (0.0)
Do you have any ongoing physical health condition?			
Yes - Both Treated and Untreated, N (%)†	293.0 (0.3)	51.0 (0.2)	242.0 (0.3)
Yes - Treated, N (%)***	409.0 (0.4)	109.0 (0.5)	300.0 (0.4)
Yes - Untreated, N (%)**	309.0 (0.3)	45.0 (0.2)	264.0 (0.3)
Do you have any ongoing physical health condition?			
Don't Know, N (%)	7.0 (0.0)	2.0 (0.0)	5.0 (0.0)
No, N (%)	268.0 (0.3)	51.0 (0.2)	217.0 (0.3)
Yes - Both Treated and Untreated, N (%)*	260.0 (0.3)	41.0 (0.2)	219.0 (0.3)
Yes - Treated, N (%)††	282.0 (0.3)	68.0 (0.3)	214.0 (0.3)
Yes - Untreated, N (%)	193.0 (0.2)	43.0 (0.2)	150.0 (0.2)
Do you live with mental illness?			

Table A.1: Baseline characteristics of study participants

Characteristic	Total (N=1,011)	Stable housed (N=205)	People with additional needs (N=806)
Yes - Both Treated and Untreated, N (%)†	293 (0.3)	54 (0.2)	239 (0.3)
Yes - Treated, N (%)***	409 (0.4)	117 (0.5)	292 (0.4)
Yes - Untreated, N (%)**	309 (0.3)	49 (0.2)	260 (0.3)
Homeless status			
Absolutely Homeless, N (%)†	786.0 (0.8)	152.0 (0.7)	634.0 (0.8)
Homeless (60 months), mean (SD)	31.1 (0.4)	31.2 (23.8)	30.9 (23.2)
Require disability accommodations? Yes, N (%)†	84.0 (0.1)	12.0 (0.1)	72.0 (0.1)
Have you been released from an institution in past 12 months?			
Correctional Facility, N (%)†	199.0 (0.2)	33.0 (0.2)	166.0 (0.2)
Healthcare Facility, N (%)	371.0 (0.4)	69.0 (0.3)	302.0 (0.4)
Mental Facility, N (%)	249.0 (0.2)	44.0 (0.2)	205.0 (0.3)
Residential Addiction Facility, N (%)	236.0 (0.2)	53.0 (0.3)	183.0 (0.2)
Healthcare Services			
Lived in health system, N (%)	741.0 (0.7)	149.0 (0.7)	592.0 (0.7)
Emergency room visits (0), mean (SD)**	3.1 (0.4)	4.1 (15.5)	2.1 (4.1)
Emergency medical service visits (0), mean (SD)***	1.6 (0.4)	2.3 (8.6)	1.0 (2.2)
Days in hospital (0), mean (SD)*	14.8 (0.4)	11.2 (27.9)	18.5 (44.2)
No. of hospital visits, mean (SD)††	2.9 (0.4)	3.5 (13.8)	2.2 (8.2)
Legal system			
In the legal system (last 12 months), N (%)†	520.0 (0.5)	95.0 (0.5)	425.0 (0.5)
Days in Jail (0), mean (SD)*	11.8 (0.4)	7.4 (31.7)	16.3 (51.0)
Times in court (0), mean (SD)††	1.0 (0.4)	0.7 (1.7)	1.3 (4.8)
What was your primary residence prior to the program?			
Addictions Treatment Facility, N (%)	83.0 (0.1)	19.0 (0.1)	64.0 (0.1)
Correctional facility, N (%)	20.0 (0.0)	3.0 (0.0)	17.0 (0.0)
Dwelling unfit for human habitation, N (%)†	10.0 (0.0)	4.0 (0.0)	6.0 (0.0)
Emergency shelter, N (%)*	381.0 (0.4)	93.0 (0.5)	288.0 (0.4)
Hospital/medical facility, N (%)***	52.0 (0.1)	1.0 (0.0)	51.0 (0.1)
Long-term housing with supports, N (%)*	5.0 (0.0)	3.0 (0.0)	2.0 (0.0)
Outside, N (%)	121.0 (0.1)	20.0 (0.1)	101.0 (0.1)
Renting - subsidized, N (%)	8.0 (0.0)	2.0 (0.0)	6.0 (0.0)
Renting - unsubsidized, N (%)††	35.0 (0.0)	11.0 (0.1)	24.0 (0.0)
Staying with family or friends (couch surfing), N (%)*	191.0 (0.2)	28.0 (0.1)	163.0 (0.2)
Transitional Housing, N (%)	79.0 (0.1)	16.0 (0.1)	63.0 (0.1)
Foster care system, N (%)††	226.0 (0.2)	37.0 (0.2)	189.0 (0.2)
Child protection services, N (%)	84.0 (0.1)	14.0 (0.1)	70.0 (0.1)
Experienced family violence, N (%)	350.0 (0.3)	68.0 (0.3)	282.0 (0.3)

Appendix B

Mapping Basic Needs to Maslow's Hierarchy

The HF Assessment form used by the CHF-HF program provides 21 "basic needs" a client can select, plus an open field for "other." Based on the values collected, there were 763 different basic needs requested by CHF-HF participants at program intake and at three-month follow-up interviews. The 763 different values provided were combined into 58 different need categories. Based on the basic needs requested by participants, need semantics in Table B.1 were identified. The complete analysis is presented in Section 6.3. Table B.1 is a duplicate of Table 6.3, provided here for convenience. Following Table B.1, this appendix provides the complete mapping of the 58 need categories to Maslow's hierarchy.

Table B.1: Basic properties of *client* needs and their relation to a service *provider* captured by the CHF-HF dataset.

Owner	**Property**	**Form Field**	**Description/Example**
Client	Need	Mapped to an MH Goal.	A basic need in Maslow's hierarchy with justification. For example, "physiological" or "security" as per definition in Table 6.2.
Client	MH Goal	A Goal mapped directly to an MH Need.	For example, "not being hungry" is goal directly linked to the "physiological" MH Need.
Client	$rank(A, s_i)$	Order of *Needs* provided in the initial and follow-up asessment questionnaires is assumed to be the agent's preferred order.	Preferred order of needs dictates how clients rank them, where earlier needs are more important than later needs at specific periods.
Client	Motivation Description	Reasons for needs expressed by client.	The description allows a practitioner to classify a need into the appropriate MH level. This was not supplied by the data, but would be provided by a client.
Client	Goal	*Basic needs assistance*, *Health information*	For example, obtaining "special formula for infant" or a "birth certificate."

Table B.1: Basic properties of *client* needs and their relation to a service *provider* captured by the CHF-HF dataset.

Owner	**Property**	**Form Field**	**Description/Example**
Client / Provider	Constraint	Context-specific like missing information, inadequate funds, or insufficient training.	A constraint is anything that prevents a client from achieving their goals. A constraint can be a functional prerequisite or a goal prerequisite.
Provider	Resource	*Service referral*, *Case worker contact*, *Income*, *Employment training and education*	A resource that is meant to be used by a client to satisfy a constraint.
Provider	Service	*Service referrals*, *Case worker contact*	Makes specific resources available to a client, such as "daycare" or "detox program."

HF Assessment to Maslow Level Mapping

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Referral							
Need		New service	Happy family	Social activities	Critical, health, family needs		Referral needs are associated with what the referral is for.
Goal		Get new or better services	Provide toys and activities for kids	Get referral to a gym	Get referral to critical services		
Motivation Description		Better self	Have socially adjusted kids	Go to recreation centre	Need referral for critical needs		
Constraint		Lack of information about where to get help next	Lack of money and activities.	Requirements not met	Requirements not met		
Resource		Information	Holiday presents, youth advocate, charity	Referral	referral		
Service		Case worker	Family services	Case worker	Case worker		
Phone			Non-Elderly (< 51)	Non-Elderly (< 51)	Elderly (51+)		
Need			Have less stress	Expand social network	Stay safe		Phone can be thought of as a esteem or physical need, but it has been identified as a non-critical need that focuses on social needs.
Goal			Pay off phone bill	Keep in touch with friends/family	Be able to call for help during an emergency		
Motivation Description			Reduce stress of owing money	Keep in touch with people more efficiently	Assistance in time of emergency.		
Constraint			Lack of money	Lack of money	Lack of money		
Resource			Case worker	Case worker	Case worker		
Service			Case worker	Case worker	Case worker		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Goods family							
Need			Family pride				In some instances, family is viewed as an extension of the individual. Providing tangible goods for family is defined as same as providing goods for self. Assuming individual is head of household.
Goal			Have a happy and safe family				
Motivation Description			Want family to be happy				
Constraint			Lack of money				
Resource			Charity, information				
Service			Family services				
Family support							
Need		Healthy family	Healthy family				Providing for one's family is not the same as being in contact with family members. The latter is a social need, while the former is a personal need.
Goal		Be a better parent	Be a better parent				
Motivation Description		Be a better parent	Be a better parent				
Constraint		Lack of parenting/family skills	Lack of parenting/family skills				
Resource		Parenting classes	Parenting classes				
Service		Family services	Family services				

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Child care							
Need			Happy Family		Basic child care needs	Physiological need for kids	Providing for family is a need relating to self, not a social need. Having a relationship for non-dependant family members is a social need.
Goal			Toys, activities, education, and counselling for kids		Provide basic needs and goods for kids	Provide emergency child care needs	
Motivation Description			Have socially adjusted kids		Basic security needs for kids	Keep kids healthy	
Constraint			Lack of money and activities		Lack of money	Lack of money	
Resource			Holiday presents, youth advocate, charity		Charity	Charity, Social worker	
Service			Family services		Family services	Family services, Child Protective Services	
Counseling							
Need			Healthy mental state	Healthy mental state	More security		Need for counselling can include: need for further analysis to identify issues; psychological trauma; history of abuse.
Goal			Identify or resolve unhealthy mental state	Identify or resolve unhealthy mental state	Get help dealing with past abuse or traumatic events, conflict situations		
Motivation Description			Feel uneasy about mental state	Feel uneasy about mental state	Feel more secure following traumatic or conflict events		
Constraint			Don't know how to resolve unhealthy mental state	Don't know how to resolve unhealthy mental state	Can't provide security conflict resolution alone		
Resource			Counselor	Counselor	Police, Counselor		
Service			Counseling	Counseling	Police, Counselor		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Case management							
Need		Improve daily life					Case management finds specific resources when moving achieving new goals.
Goal		Get help finding resources					
Motivation Description		Improve daily life					
Constraint		Lack of information					
Resource		Information					
Service		Case manager					
Social family							
Need				Social events for children			Social events for family of dependants is related to social needs of self.
Goal				Find social activities for children			
Motivation Description				Social family			
Constraint				Lack of money; don't know where or how to find activities			
Resource				Family worker, charity			
Service				Family services			

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Social							
Need		Improve life		Be more social			Social needs can be for everyday activities (Social) or for self-improvement (Self-Actualization)
Goal		Find a mentor		Have more opportunities for social activities			
Motivation Description		Want to better self		Do more social activities, recreationally			
Constraint		Don't know anyone to be a mentor		Trouble being social			
Resource		Information		Counseling			
Service		Social worker		Counselor			
Aboriginal / Indigenous							
Need				Connect with community			Due to recent trend in referring Indigenous clients to community-based Indigenous services, this is type of need is a social need.
Goal				Gain access to aboriginal-specific services			
Motivation Description				Connect with aboriginal community			
Constraint				Limited aboriginal-specific services			
Resource				Aboriginal-specific needs			
Service				Aboriginal Community			

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Goods infant							
Need			Healthier family		Healthy family		Infant are dependants, so their needs are extensions of the individual.
Goal			Get help finding better job		Get supplies baby needs to be healthy		
Motivation Description			Healthier baby		Healthy baby		
Constraint			Don’t know where to look for job		Lack of goods and money		
Resource			Vocational worker		Money, charity		
Service			Vocational worker		Family services		
Disability support			*Relatively homeless*	*Relatively homeless*	*Absolutely homeless*		
Need			Live healthy life with disability	Live healthy life with disability	Live healthy life with disability		Disability needs are a security need for absolutely homeless as any unmet disability need is a critical need that impacts their safety. Relatively homeless require disability support but it is not a security risk.
Goal			Need help with application for disability income/funding	Need help with application for disability income/funding	Need help with application for disability income/funding		
Motivation Description			Maintain quality of life despite disability	Maintain quality of life despite disability	Maintain quality of life despite disability		
Constraint			Don't know how to get funding	Don't know how to get funding	Don't know how to get funding		
Resource			Healthcare worker	Healthcare worker	Healthcare worker		
Service			Healthcare worker	Healthcare worker	Healthcare worker		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Advocacy help							
Need					Reduce stress		Non-legal advocacy.
Goal					Get help resolving outstanding critical issues		
Motivation Description					Resolving critical issues		
Constraint					Don't have conflict resolution skills		
Resource					Case manager		
Service					Case manager		
Advocacy legal							
Need					Reduce stress		Legal advocacy represents any need for assistance in legal matters that can impact a client's safety or stability.
Goal					Get help resolving legal matters and related issues like attending court, legal fees, advocacy, and guidance		
Motivation Description					Resolve legal issues		
Constraint					Lack of information, courage, money		
Resource					Legal worker		
Service					Legal aid		

Maslow Levels	**None**	**Self-Actualization**	**Esteem**	**Social**	**Security**	**Physiological**	**Comments**
GoalNeed							
Housing temp					*Relative homeless*	*Absolute homeless*	
Need					Shelter	Shelter	Housing needs differ for absolutely and relatively homeless. For absolutely homeless it is a physiological need while for relatively it is a security need.
Goal					Temporarily need housing	Temporarily need housing	
Motivation Description					Help find housing for short-term stay	Help find housing for short-term stay	
Constraint					Don't know where shelters have available room.	Don't know where shelters have available room.	
Resource					Social worker	Social worker	
Service					Temporary bed	Temporary bed	
Addiction support							
Need		Stay healthy				Be healthy	Short-term goals are Physiological while long-term addiction support is a Self-Actualization need.
Goal		Get help staying sober				Find help getting sober	
Motivation Description		Stay sober and healthy, and self-reliant				Get sober and be healthy	
Constraint		Determination, self-discipline, lack of service				Determination, self-discipline	
Resource		Counselling				Counselling	
Service		Post-detox program				Detox program	

Remaining SPDAT to Maslow Level Mapping

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Tenant insurance. support							
Need			Money and housing for long term		Stable living		
Goal			Get help with long-term housing needs from landlord; flood, landlord mediation		Get help negotiating with landlord about lease		
Motivation Description			Long-term housing planning		Safe place to live		
Constraint			Can't negotiate with landlord		Can't negotiate with landlord		
Resource			Housing worker		Housing worker		
Service			Housing worker		Housing worker		
Money planning							
Need			Handle money				
Goal			Be better with managing money				
Constraint			Lack of experience managing money				
Resource			Financial planning				
Service			Case worker				

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Immigrant services							
Need				Expand social network	Feel safe		
Goal				Finalize immigration status	Finalize immigration status		
Motivation Description				Participate in society	Legal certainty		
Constraint				Can't participate in all aspects of society			
Resource				Case worker	Case worker		
Service				Case worker	Case worker		
Identification							
Need			Other services		Health services		
Goal			Gain access to services that require identification		Gain access to health services		
Motivation Description			Able to get more services		Health card		
Constraint			Don't know where to get identification		Don't know where to get identification		
Resource			ID services		ID services		
Service			Case worker		Case worker		
Home goods							
Need					Security		
Goal					Get help to have a functional home		
Motivation Description					Have a safe place to live		
Constraint					Home is not functional		
Resource					Money		
Service					Housing worker		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Goods misc.							
Need		Various needs	Feel good with others		Feel safe and secure		
Goal		Feel comfortable	Gain access to cosmetics		Get non-essential goods.		
Motivation Description		Get various non-essential goods	Cosmetics		Clothing, rent subsidy, security		
Constraint		Lack of money, information	Lack of money		Lack of money, information		
Resource		The goods, charity	Charity		Charity		
Service		Social worker	Social worker		Social worker		
Education							
Need		Improve life	Improve esteem	Communicate with others			
Goal		Get into school program	Get into school program	Take language classes			
Motivation Description		Better self	Feel better about self	Communicate with others, get services			
Constraint		Don't have enough information	Don't have enough information	Don't know where, lack of money			
Resource		Information	Information	Language school			
Service		Education worker	Education worker	Case worker			

Maslow Levels GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Forms							
Need			Social, security, physiological	Social participation	Feel secure		
Goal			Get entitled income; get more services	Fill out forms to social centre and for miscellaneous advocacy.	Get help filling out rent and health forms		
Motivation Description			Need new services	YMCA forms, advocacy forms	Rent and health advocacy forms		
Constraint			Don't know regulations, don't have backup documents	Don't know regulations; don't have backup documents	Don't know regulations; don't have backup documents		
Resource			Information	Information	Information		
Service			Social worker	Social worker	Housing worker, Healthcare worker		
Debt reduction							
Need			Reduce stress		Feel more secure about essential services		
Goal			Get money to pay off debt		Get money to pay off legal/health debt		
Motivation Description			Reduce misc debt		Reduce legal/medical fees		
Constraint			Lack of money		Lack of money		
Resource			Charity, money		Charity, money		
Service			Financial assistance		Financial assistance		

Maslow Levels	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
GoalNeed							
Computer							
Need			Be social	Be social			
Goal			Have access to a computer	Have access to a computer			
Motivation Description			Reach out to others	Reach out to others			
Constraint			Lack of money	Lack of money			
Resource			Donated computer, computer lab	Donated computer, computer lab			
Service			Social worker	Social worker			
Transportation							
Need			Need to go to misc events	Need to go to social events	Need to complete essential travel		
Goal			Get transportation or money	Get transportation or money	Get transportation or money		
Motivation Description			Meet with social circle	Meet with social circle	Need to go to work, for essential shopping, or from hospital		
Constraint			Lack of transportation or money	Lack of transportation or money	Lack of transportation or money		
Resource			Money, bus, taxi, volunteer	Money, bus, taxi, volunteer	Money, bus, taxi, volunteer		
Service			Social worker	Social worker	Social worker		
Housing goods							
Need					Safe home		
Goal					Have a usable home		
Motivation Description					Livable home		
Constraint					Lack of money		
Resource					Charity, goods		
Service					Housing worker		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Furniture							
Need					Functional home		
Goal					Get furniture		
Motivation Description					Livable home		
Constraint					Lack of money, don't know where to get furniture		
Resource					Money, information		
Service					Housing worker		
Employment Training							
Need		Build up self-esteem	Build up self-esteem				
Goal		Get vocational training for a better job	Get vocational training for a better job				
Motivation Description		Get better job, build self-esteem, and get more money	Get better job, build self-esteem, and get more money				
Constraint		Lack of money, don't know what to train in	Lack of money, don't know what to train in				
Resource		Vocational training	Vocational training				
Service		Vocational worker	Vocational worker				

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Money social							
Need			Social engagement	Social engagement			
Goal			Get money for social activities	Get money for social activities			
Motivation Description			Be more social	Be more social			
Constraint			Lack of money	Lack of money			
Resource			Charity, advocacy	Charity, advocacy			
Service			Social worker	Social worker			
Money family							
Need			Children social needs	Children social needs			
Goal			Find money for recreational activities for children	Find money for children's rec activities			
Motivation Description			Happy family	Happy family			
Constraint			Lack of money; don't know where or how to find activities	Lack of money; don't know where or how to find activities			
Resource			Family worker	Family worker			
Service			Family services	Family services			
Mental Health Conditions							
Need				Reduce stress due to social loss	Reduce mental problems		
Goal				Get grief counseling	Get counseling for mental problems		
Motivation Description				Need to reduce grief	Be better at managing life with mental problems		
Constraint				don't know how to reduce grief	Don't know how to manage mental problems		
Resource				Grief counseling	Counseling		
Service				Counselor	Counselor		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Life skills							
Need		Social interaction	Social interaction	Social interaction			
Goal		Learn how to be more social	Learn how to be more social	Learn how to be more social without conflict			
Motivation Description		Learn life skills	Learn life skills	Learn life skills and conflict resolution			
Constraint		don't know how to interact with others	don't know how to interact with others	don't know how to handle bad situations			
Resource		Counselor	Counselor	Counselor			
Service		Counselor	Counselor	Counselor			
Hygiene							
Need			Be accepted by society	Be accepted by society	Safe home		
Goal			Get and learn how to use personal hygiene products	Get and learn how to use personal hygiene products	Help keeping home clean and livable		
Motivation Description			Want to be more hygienic	Want to be more hygienic	Have a clean home		
Constraint			Don't have hygiene products or maintain hygiene	Don't have hygiene products or maintain hygiene	Lack of money; don’t know how		
Resource			Get hygienic products	Get hygienic products	Charity; volunteers		
Service			Shelter	Shelter	Shelter		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Clean Clothes							
Need			Feel safe with others	Feel safe with others	Feel safe with others		
Goal			Get laundry, have clean clothing	Get laundry, have clean clothing	Get laundry Have clean clothing		
Motivation Description			Want to have clean clothes	Want to have clean clothes	Want to have clean clothes		
Constraint			Lack of money	Lack of money	Lack of money		
Resource			Laundry services	Laundry services	Laundry services		
Service			Shelter	Shelter	Shelter		
Utility arrears							
Need				Maintain social network	Keep home livable		
Goal				Get help paying phone bill	Keep home livable		
Motivation Description				Keep in touch with family/friends	Retain housing- or city-services required for living		
Constraint				Lack of money	Lack of money		
Resource				Bill relief, advocacy, charity	Bill relief, advocacy, charity		
Service				Case worker	Housing worker		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Security deposit							
Need					Need shelter		
Goal					Get money to pay for security deposit		
Motivation Description					Want to start living in home		
Constraint					Lack of money		
Resource					Bill relief, advocacy, charity		
Service					Housing worker		
Rent shortfall / subsidy							
Need					Need shelter		
Goal					Get money to keep my home		
Motivation Description					Want to keep my home		
Constraint					Lack of money		
Resource					Bill relief, advocacy, charity		
Service					Housing worker		
Rent arrears							
Need					Need shelter and other needs		
Goal					Get help to pay outstanding rent debt		
Motivation Description					Keep home and reduce stress		
Constraint					Lack of money		
Resource					Bill relief, advocacy, charity		
Service					Housing worker		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Money goods							
Need					Have misc. goods		
Goal					Get money for misc. goods from store		
Motivation Description					Purchase misc. goods from store		
Constraint					Lack of money		
Resource					Charity, money		
Service					Social worker		
Income							
Need					Stability		
Goal					Get help finding source of income		
Motivation Description					Need long-term income		
Constraint					Don't know how to find source of income		
Resource					Case worker		
Service					Case worker		
Housing supplement							
Need					Keep long-term shelter		
Goal					Get extra income to help with rent		
Motivation Description					Need to retain home		
Constraint					Lack of money		
Resource					Bill relief, advocacy, charity		
Service					Housing worker		

Maslow Levels / **GoalNeed**	**None**	**Self-Actualization**	**Esteem**	**Social**	**Security**	**Physiological**	**Comments**
Housing maintenance							
Need					Repair long-term shelter		
Goal					Get extra income to help with crucial home repairs and maintenance		
Motivation Description					Need to repair and maintain home safety		
Constraint					Lack of money		
Resource					Bill relief, advocacy, charity		
Service					Housing worker		
Housing					*Relative homeless*	*Absolute homeless*	
Need					Need shelter	Need shelter	
Goal					Get help finding a home	Get help finding a home	
Motivation Description					Need to find a home	Need to find a home	
Constraint					Don't know where or how to find a home	Don't know where or how to find a home	
Resource					Information	Information	
Service					Housing worker	Housing worker	

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Clothing							
Need					Clothing		
Goal					Get help buying or receiving clothing		
Motivation Description					Be clothed		
Constraint					Lack of money		
Resource					Charity		
Service					Donation centre		
Medication							
Need					Be healthy		
Goal					Help getting medication		
Motivation Description					Have high quality of life despite of health problems		
Constraint					Lack of money or access to health services		
Resource					Healthcare worker		
Service					Healthcare worker		

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Health support							
Need				Be social in a healthy environment	Misc. health needs		
Goal				Join a gym	Help finding healthcare		
Motivation Description				Stay healthy and be social	Stay healthy		
Constraint				Don't know where or how to get membership	Don't know where or how to get healthcare		
Resource				gym membership	Dentist, nursing support, eye glasses, wheelchair, Dr. appt, palliative care recreational therapy		
Service				Social worker	Healthcare worker		
Money health							
Need					Misc. health needs		
Goal					Get money for health services		
Motivation Description					Stay healthy		
Constraint					Lack of money		
Resource					Money		
Service					Case worker		
Food							
Need						Food	
Goal						Receive food assistance	
Motivation Description						Get food	
Constraint						Lack of money	
Resource						Food, money	
Service						Meal program	

Maslow Levels / GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Don't know							
Need					Unknown basic need is unsatisfied		
Goal					Help understanding and satisfying basic need		
Motivation Description					Need something, not sure what		
Constraint					Don't know what it is		
Resource					Information and advocacy		
Service					Social worker		
None							
Need	None						
Goal	None						
Motivation Description	None						
Constraint	None						
Resource	Everything is available						
Service	None						
Declined to answer							
Need	Unknown						
Goal	Unknown						
Motivation Description	Unknown						
Constraint	Unknown						
Resource	Unknown						
Service	Unknown						

Maslow Levels GoalNeed	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
Housing safety							
Need					Safe home		
Goal					Get exterminator		
Motivation Description					Have a safe and clean home		
Constraint					Lack of money		
Resource					Housing worker		
Service					Housing worker		
Miscellaneous. support							
Need				Community engagement			
Goal				Get help with non-critical needs like temporary storage, fax machine, pet deposit, etc			
Motivation Description				Need to satisfy non-critical needs			
Constraint				Lack of money			
Resource				Social worker			
Service				Social worker			
Moving							
Need					Safe and secure home		
Goal					Get help with moving and storage arrangements		
Motivation Description					Move to a better home		
Constraint					Lack of money and help		
Resource					Housing worker		
Service					Housing worker		
Security							

Maslow Levels	None	Self-Actualization	Esteem	Social	Security	Physiological	Comments
GoalNeed							
Need					More security		
Goal					Get help with past violent/sexual abuse		
Motivation Description					Feel more secure after traumatic events		
Constraint					Can't provide security alone		
Resource					Police		
Service					Police		

Appendix C

Planning Problem: Action Schema

Based on the types of needs captured by CHF-HF data, a set of services can be associated with each need. The following action schema captures these relationships. It is presented in STRIPS format. The action schema presented here is the full listing for the homeless client planning problem in experiment discussed in Chapter 7.

Employment training

Action 1 (Get emp training info)**.**

$$
\begin{aligned}
&Action(get\_emp\_training\_info(voc\_worker, ID, est)) && \text{(A-1.a)}\\
&\quad Pre: [not(A, employment\_training(ID, est)), at(A, voc\_worker), not(A, money)] && \text{(A-1.b)}\\
&\quad Add: [info(A, employment\_training(ID, est))] && \text{(A-1.c)}\\
&\quad Delete: [] && \text{(A-1.d)}\\
&)
\end{aligned}
$$

Action 2 (Training program info)**.**

$$
\begin{aligned}
&Action(training\_program\_info(voc\_worker, ID, est)) && \text{(A-2.a)}\\
&\quad Pre: [not(A, employment\_training(ID, est) && \text{(A-2.b)}\\
&\qquad\quad info(A, employment\_training(ID, est)),\\
&\qquad\quad at(A, voc\_worker),\\
&\qquad\quad not(A, money)]),\\
&\quad Add: [info(A, training\_program(ID, est))] && \text{(A-2.c)}\\
&\quad Delete: [] && \text{(A-2.d)}\\
&)
\end{aligned}
$$

Action 3 (Training signup)**.**

$$
\begin{aligned}
&Action(training\_signup(voc\_worker, ID, est)) && \text{(A-3.a)}\\
&\quad Pre: [not(A, employment\_training(ID, est)), info(A, training\_program(ID, est) && \text{(A-3.b)}\\
&\qquad\quad info(A, employment\_training(ID, est)),\\
&\qquad\quad at(A, voc\_worker),\\
&\qquad\quad not(A, money)]),\\
&\quad Add: [t(A, training\_signup(ID, est))] && \text{(A-3.c)}\\
&\quad Delete: [info(A, employment\_training(ID, est)), info(A, training\_program(ID, est))] && \text{(A-3.d)}\\
&)
\end{aligned}
$$

Action 4 (Start training program)**.**

$$
\begin{aligned}
&Action(start\_training\_program(voc\_school, ID, est)) && \text{(A-4.a)}\\
&\quad Pre: [not(A, employment\_training(ID, est)), t(A, training\_signup(ID, est) && \text{(A-4.b)}\\
&\qquad\quad at(A, voc\_school),\\
&\qquad\quad not(A, money)]),
\end{aligned}
$$

$Add: [t(A, employment\_training(ID, est))]$ (A-4.c)
$Delete: [t(A, training\_signup(ID, est)), not(A, employment\_training(ID, est))]$ (A-4.d)
)

Action 5 (Start training program).

$Action(start\_training\_program(voc\_school, ID, self))$ (A-5.a)
$Pre: [not(A, employment\_training(ID, self)), t(A, training\_signup(ID, est)$ (A-5.b)
$at(A, voc\_school),$
$not(A, money)]),$
$Add: [t(A, employment\_training(ID, self))]$ (A-5.c)
$Delete: [not(A, employment\_training(ID, self))]$ (A-5.d)
)

Income

Action 6 (Get income source info).

$Action(get\_income\_source\_info(case\_worker, ID))$ (A-6.a)
$Pre: [at(A, case\_worker), not(A, income(ID))]$ (A-6.b)
$Add: [info(A, income\_source(ID))]$ (A-6.c)
$Delete: []$ (A-6.d)
)

Action 7 (Use income source info).

$Action(use\_income\_source\_info(case\_worker, ID))$ (A-7.a)
$Pre: [info(A, income\_source(ID)), not(A, income(ID)), at(A, case\_worker)]$ (A-7.b)
$Add: [t(A, apply\_income\_source\_info(ID))]$ (A-7.c)
$Delete: []$ (A-7.d)
)

Action 8 (Get income).

$Action(get\_income(ID))$ (A-8.a)
$Pre: [at(A, ID), t(A, apply\_income\_source\_info(ID)), not(A, income(ID))]$ (A-8.b)
$Add: [t(A, income(ID))]$ (A-8.c)
$Delete: [not(A, income(ID))]$ (A-8.d)
)

Utility arrears

Action 9 (Get utility pay info).

$Action(get\_utility\_pay\_info(case\_worker, ID, MH))$ (A-9.a)
$Pre: [at(A, case\_worker), not(A, money), t(A, utility\_arrears(ID, MH))]$ (A-9.b)
$Add: [t(A, utility\_pay\_info(utility\_charity, ID, MH))]$ (A-9.c)
$Delete: [not(A, utility\_pay\_info(utility\_charity, ID, MH))]$ (A-9.d)
)

Action 10 (Get utility pay at utility charity).

$Action(get\_utility\_pay\_at(utility\_charity, ID, MH))$ (A-10.a)
$Pre: [t(A, utility\_arrears(ID, MH)$ (A-10.b)
$t(A, utility\_pay\_info(utility\_charity, ID, MH)),$
$at(A, utility\_charity),$
$not(A, money)]),$
$Add: [not(A, utility\_arrears(ID, MH))]$ (A-10.c)
$Delete: [t(A, utility\_arrears(ID, MH))]$ (A-10.d)
)

Action 11 (Pay utility w money).

$$Action(pay\_utility\_w\_money(bank, ID, MH)) \tag{A-11.a}$$
$$Pre: [at(A, bank), t(A, money), t(A, utility\_arrears(ID, MH))] \tag{A-11.b}$$
$$Add: [not(A, utility\_arrears(ID, MH)), not(A, money)] \tag{A-11.c}$$
$$Delete: [t(A, utility\_arrears(ID, MH)), t(A, money)] \tag{A-11.d}$$
)

Clothing

Action 12 (Get clothing info).

$$Action(get\_clothing\_info(charity, ID)) \tag{A-12.a}$$
$$Pre: [at(A, charity), not(A, money), not(A, clothing(ID))] \tag{A-12.b}$$
$$Add: [t(A, clothing\_info(donation\_cntr, ID))] \tag{A-12.c}$$
$$Delete: [not(A, clothing\_info(charity, ID))] \tag{A-12.d}$$
)

Action 13 (Get clothing at donation cntr).

$$Action(get\_clothing\_at(donation\_cntr, ID)) \tag{A-13.a}$$
$$\begin{aligned}Pre: [&not(A, clothing(ID)), t(A, clothing\_info(donation\_cntr, ID)\\ &at(A, donation\_cntr),\\ &not(A, money)]),\end{aligned} \tag{A-13.b}$$
$$Add: [t(A, clothing(ID))] \tag{A-13.c}$$
$$Delete: [not(A, clothing(ID))] \tag{A-13.d}$$
)

Moving

Action 14 (Receive moving advocacy from housing worker).

$$Action(receive\_moving\_advocacy\_from(housing\_worker, ID, HID)) \tag{A-14.a}$$
$$\begin{aligned}Pre: [&not(A, moving\_resources(ID, HID)), at(A, housing\_worker), not(A, money\\ &t(A, have\_longterm\_housing(HID))]),\end{aligned} \tag{A-14.b}$$
$$Add: [info(A, moving\_advocacy(housing\_worker, ID, HID))] \tag{A-14.c}$$
$$Delete: [] \tag{A-14.d}$$
)

Action 15 (Receive moving info from housing worker).

$$Action(receive\_moving\_info\_from(housing\_worker, ID, HID)) \tag{A-15.a}$$
$$\begin{aligned}Pre: [&not(A, moving\_resources(ID, HID)\\ &info(A, moving\_advocacy(housing\_worker, ID, HID)),\\ &at(A, housing\_worker),\\ &not(A, money),\\ &t(A, have\_longterm\_housing(HID))]),\end{aligned} \tag{A-15.b}$$
$$Add: [info(A, moving\_volunteer(ID, HID))] \tag{A-15.c}$$
$$Delete: [info(A, moving\_advocacy(housing\_worker, ID, HID))] \tag{A-15.d}$$
)

Action 16 (Use moving support).

$$Action(use\_moving\_support(housing\_worker, ID, HID)) \tag{A-16.a}$$
$$\begin{aligned}Pre: [&not(A, moving\_resources(ID, HID)), info(A, moving\_volunteer(ID, HID)\\ &not(A, money),\\ &at(A, housing\_worker),\\ &t(A, have\_longterm\_housing(HID))]),\end{aligned} \tag{A-16.b}$$
$$Add: [t(A, moving\_volunteer(ID, HID))] \tag{A-16.c}$$
$$Delete: [info(A, moving\_volunteer(ID, HID))] \tag{A-16.d}$$
)

Action 17 (Moving).

$$Action(moving(ID, HID)) \tag{A-17.a}$$
$$Pre : [t(A, moving\_volunteer(ID, HID)), at(A, home), not(A, money) \tag{A-17.b}$$
$$t(A, have\_longterm\_housing(HID))]),$$
$$Add : [t(A, moving\_resources(ID, HID))] \tag{A-17.c}$$
$$Delete : [not(A, moving\_resources(ID, HID)), t(A, moving\_volunteer(ID, HID))] \tag{A-17.d}$$
)

Rent arrears

Action 18 (Get rent arrears help advocacy).

$$Action(get\_rent\_arrears\_help\_advocacy(housing\_worker, HID, ID)) \tag{A-18.a}$$
$$Pre : [t(A, rent\_arrears\_help(HID, ID)), t(A, have\_longterm\_housing(HID) \tag{A-18.b}$$
$$at(A, housing\_worker),$$
$$not(A, money)]),$$
$$Add : [info(A, rent\_arrears\_help\_advocacy(HID))] \tag{A-18.c}$$
$$Delete : [] \tag{A-18.d}$$
)

Action 19 (Get rent arrears help relief).

$$Action(get\_rent\_arrears\_help\_relief(charity, HID, ID)) \tag{A-19.a}$$
$$Pre : [info(A, rent\_arrears\_help\_advocacy(HID) \tag{A-19.b}$$
$$t(A, have\_longterm\_housing(HID)),$$
$$not(A, money),$$
$$at(A, charity),$$
$$t(A, rent\_arrears\_help(HID, ID))]),$$
$$Add : [not(A, rent\_arrears\_help(HID, ID))] \tag{A-19.c}$$
$$Delete : [t(A, rent\_arrears\_help(HID, ID))] \tag{A-19.d}$$
)

Action 20 (Get rent arrears help charity).

$$Action(get\_rent\_arrears\_help\_charity(charity, HID, ID)) \tag{A-20.a}$$
$$Pre : [info(A, rent\_arrears\_help\_advocacy(HID) \tag{A-20.b}$$
$$t(A, have\_longterm\_housing(HID)),$$
$$not(A, money),$$
$$at(A, charity),$$
$$t(A, rent\_arrears\_help(HID, ID))]),$$
$$Add : [info(A, charity\_rent\_arrears\_help\_money(charity, ID))] \tag{A-20.c}$$
$$Delete : [] \tag{A-20.d}$$
)

Action 21 (Pay rent arrears help).

$$Action(pay\_rent\_arrears\_help(charity, HID, ID)) \tag{A-21.a}$$
$$Pre : [not(A, money), info(A, rent\_arrears\_help\_advocacy(HID) \tag{A-21.b}$$
$$info(A, charity\_rent\_arrears\_help\_money(charity, ID)),$$
$$t(A, have\_longterm\_housing(HID)),$$
$$t(A, rent\_arrears\_help(HID, ID))]),$$
$$Add : [not(A, rent\_arrears\_help(HID, ID))] \tag{A-21.c}$$
$$Delete : [info(A, rent\_arrears\_help\_advocacy(HID) \tag{A-21.d}$$
$$info(A, charity\_rent\_arrears\_help\_money(charity, ID)),$$
$$t(A, rent\_arrears\_help(HID, ID))]),$$
)

Action 22 (Get rent arrears help money).

$$Action(get\_rent\_arrears\_help\_money(housing\_worker, HID, ID)) \tag{A-22.a}$$
$$Pre : [t(A, rent\_arrears\_help(HID, ID)), at(A, housing\_worker \tag{A-22.b}$$
$$t(A, have\_longterm\_housing(HID)),$$

$not(A, money)]),$
$Add : [t(A, money)]$ (A-22.c)
$Delete : [not(A, money)]$ (A-22.d)
)

Action 23 (Pay rent arrears help).

$Action(pay\_rent\_arrears\_help(money, HID, ID))$ (A-23.a)
$Pre : [t(A, money), t(A, have\_longterm\_housing(HID)$ (A-23.b)
$t(A, rent\_arrears\_help(HID, ID))]),$
$Add : [not(A, money), not(A, rent\_arrears\_help(HID, ID))]$ (A-23.c)
$Delete : [t(A, money), t(A, rent\_arrears\_help(HID, ID))]$ (A-23.d)
)

Tenant insurance support

Action 24 (Get help negotiate w landlord).

$Action(get\_help\_negotiate\_w\_landlord(housing\_worker, sec, HID, ID))$ (A-24.a)
$Pre : [at(A, housing\_worker), t(A, have\_longterm\_housing(HID)$ (A-24.b)
$not(A, safe(have\_longterm\_housing(HID),$
$ID)),$
$not(A, can\_negotiate\_with\_landlord(A, sec))]),$
$Add : [t(A, can\_negotiate\_with\_landlord(housing\_worker, sec))]$ (A-24.c)
$Delete : []$ (A-24.d)
)

Action 25 (Negotiate w landlord).

$Action(negotiate\_w\_landlord(housing\_worker, sec, HID, ID))$ (A-25.a)
$Pre : [at(A, landlord), t(A, have\_longterm\_housing(HID)$ (A-25.b)
$not(A, safe(have\_longterm\_housing(HID),$
$ID)),$
$t(A, can\_negotiate\_with\_landlord(housing\_worker, sec)),$
$not(A, can\_negotiate\_with\_landlord(A, sec))]),$
$Add : [t(A, tenant\_ins\_support(sec, HID, ID)$ (A-25.c)
$t(A, safe(have\_longterm\_housing(HID),$
$ID))]),$
$Delete : [not(A, tenant\_ins\_support(sec, HID, ID)$ (A-25.d)
$not(A, safe(have\_longterm\_housing(HID),$
$ID))]),$
)

Action 26 (Get help negotiate w landlord).

$Action(get\_help\_negotiate\_w\_landlord(housing\_worker, est, HID, ID))$ (A-26.a)
$Pre : [at(A, housing\_worker), t(A, have\_longterm\_housing(HID)$ (A-26.b)
$not(A, reliable(have\_longterm\_housing(HID),$
$ID)),$
$not(A, can\_negotiate\_with\_landlord(A, est))]),$
$Add : [t(A, can\_negotiate\_with\_landlord(housing\_worker, est))]$ (A-26.c)
$Delete : []$ (A-26.d)
)

Action 27 (Negotiate w landlord).

$Action(negotiate\_w\_landlord(housing\_worker, est, HID, ID))$ (A-27.a)
$Pre : [at(A, landlord), t(A, have\_longterm\_housing(HID)$ (A-27.b)
$not(A, reliable(have\_longterm\_housing(HID),$
$ID)),$
$t(A, can\_negotiate\_with\_landlord(housing\_worker, est)),$
$not(A, can\_negotiate\_with\_landlord(A, est))]),$

$$Add : [t(A, tenant\_ins\_support(est, HID, ID) \quad t(A, reliable(have\_longterm\_housing(HID), ID))]), \tag{A-27.c}$$
$$Delete : [not(A, tenant\_ins\_support(est, HID, ID) \quad not(A, reliable(have\_longterm\_housing(HID), ID))]), \tag{A-27.d}$$
)

Aboriginal

Action 28 (Referral for aboriginal services)**.**

$$Action(referral\_for\_aboriginal\_services(aboriginal\_community, ID)) \tag{A-28.a}$$
$$Pre : [at(A, aboriginal\_community)] \tag{A-28.b}$$
$$Add : [t(A, info\_aboriginal\_service(ID))] \tag{A-28.c}$$
$$Delete : [] \tag{A-28.d}$$
)

Health support

Action 29 (Get gym membership money)**.**

$$Action(get\_gym\_membership\_money(social\_worker)) \tag{A-29.a}$$
$$Pre : [not(A, healthy\_social), at(A, social\_worker), not(A, money \quad not(A, gym\_membership)]), \tag{A-29.b}$$
$$Add : [t(A, money)] \tag{A-29.c}$$
$$Delete : [not(A, money)] \tag{A-29.d}$$
)

Action 30 (Get gym membership)**.**

$$Action(get\_gym\_membership(social\_worker)) \tag{A-30.a}$$
$$Pre : [not(A, healthy\_social), at(A, social\_worker), not(A, money \quad not(A, gym\_membership)]), \tag{A-30.b}$$
$$Add : [t(A, gym\_membership)] \tag{A-30.c}$$
$$Delete : [not(A, gym\_membership)] \tag{A-30.d}$$
)

Action 31 (Get gym membership)**.**

$$Action(get\_gym\_membership(gym)) \tag{A-31.a}$$
$$Pre : [not(A, healthy\_social), at(A, gym), t(A, money), not(A, gym\_membership)] \tag{A-31.b}$$
$$Add : [t(A, gym\_membership)] \tag{A-31.c}$$
$$Delete : [not(A, gym\_membership)] \tag{A-31.d}$$
)

Action 32 (Join gym))**.**

$$Action(join\_gym) \tag{A-32.a}$$
$$Pre : [not(A, healthy\_social), at(A, gym), t(A, gym\_membership)] \tag{A-32.b}$$
$$Add : [t(A, healthy\_social)] \tag{A-32.c}$$
$$Delete : [not(A, healthy\_social)] \tag{A-32.d}$$
)

Debt reduction

Action 33 (Get debt money)**.**

$$Action(get\_debt\_money(fin\_asst, sec, ID)) \tag{A-33.a}$$
$$Pre : [t(A, have\_debt(sec, ID)), not(A, money), at(A, fin\_asst \quad not(A, get\_debt\_money(fin\_asst, sec, ID))]), \tag{A-33.b}$$
$$Add : [t(A, money)] \tag{A-33.c}$$
$$Delete : [not(A, money), not(A, get\_debt\_money(fin\_asst, sec, ID))] \tag{A-33.d}$$

)

Action 34 (Get debt money).

$$Action(get\_debt\_money(fin\_asst, est, ID)) \tag{A-34.a}$$
$$Pre : [t(A, have\_debt(est, ID)), not(A, money), at(A, fin\_asst \\ not(A, get\_debt\_money(fin\_asst, est, ID))]), \tag{A-34.b}$$
$$Add : [t(A, money)] \tag{A-34.c}$$
$$Delete : [not(A, money), not(A, get\_debt\_money(fin\_asst, est, ID))] \tag{A-34.d}$$
)

Action 35 (Get debt charity).

$$Action(get\_debt\_charity(fin\_asst, sec, ID)) \tag{A-35.a}$$
$$Pre : [t(A, have\_debt(sec, ID)), not(A, money), at(A, fin\_asst \\ not(A, get\_debt\_money(fin\_asst, sec, ID))]), \tag{A-35.b}$$
$$Add : [info(A, have\_charity\_money(charity))] \tag{A-35.c}$$
$$Delete : [] \tag{A-35.d}$$
)

Action 36 (Get debt charity).

$$Action(get\_debt\_charity(fin\_asst, est, ID)) \tag{A-36.a}$$
$$Pre : [t(A, have\_debt(est, ID)), not(A, money), at(A, fin\_asst \\ not(A, get\_debt\_money(fin\_asst, est, ID))]), \tag{A-36.b}$$
$$Add : [info(A, have\_charity\_money(charity))] \tag{A-36.c}$$
$$Delete : [] \tag{A-36.d}$$
)

Action 37 (Pay off debt).

$$Action(pay\_off\_debt(money, sec, ID)) \tag{A-37.a}$$
$$Pre : [t(A, have\_debt(sec, ID)), t(A, money)] \tag{A-37.b}$$
$$Add : [not(A, money), not(A, have\_debt(sec, ID))] \tag{A-37.c}$$
$$Delete : [t(A, money), t(A, have\_debt(sec, ID))] \tag{A-37.d}$$
)

Action 38 (Pay off debt).

$$Action(pay\_off\_debt(money, est, ID)) \tag{A-38.a}$$
$$Pre : [t(A, have\_debt(est, ID)), t(A, money)] \tag{A-38.b}$$
$$Add : [not(A, money), not(A, have\_debt(est, ID))] \tag{A-38.c}$$
$$Delete : [t(A, money), t(A, have\_debt(est, ID))] \tag{A-38.d}$$
)

Action 39 (Pay off debt).

$$Action(pay\_off\_debt(charity, sec, ID)) \tag{A-39.a}$$
$$Pre : [t(A, have\_debt(sec, ID)), info(A, have\_charity\_money(charity))] \tag{A-39.b}$$
$$Add : [not(A, have\_debt(sec, ID))] \tag{A-39.c}$$
$$Delete : [t(A, have\_debt(sec, ID))] \tag{A-39.d}$$
)

Action 40 (Pay off debt).

$$Action(pay\_off\_debt(charity, est, ID)) \tag{A-40.a}$$
$$Pre : [t(A, have\_debt(est, ID)), info(A, have\_charity\_money(charity))] \tag{A-40.b}$$
$$Add : [not(A, have\_debt(est, ID))] \tag{A-40.c}$$
$$Delete : [t(A, have\_debt(est, ID))] \tag{A-40.d}$$
)

Housing temp

Action 41 (Secure bed).

$$Action(secure\_bed(ID, phys)) \tag{A-41.a}$$
$$Pre : [abs\_homeless(A), not(A, temp\_bed(ID)), at(A, social\_worker)] \tag{A-41.b}$$
$$Add : [info(A, booked\_bed(ID))] \tag{A-41.c}$$
$$Delete : [] \tag{A-41.d}$$
)

Action 42 (Claim bed).

$$Action(claim\_bed(ID, phys)) \tag{A-42.a}$$
$$Pre : [abs\_homeless(A), not(A, temp\_bed(ID)), info(A, booked\_bed(ID)), at(A, ID)] \tag{A-42.b}$$
$$Add : [t(A, temp\_bed(ID, phys))] \tag{A-42.c}$$
$$Delete : [not(A, temp\_bed(ID)), info(A, booked\_bed(ID))] \tag{A-42.d}$$
)

Action 43 (Secure bed).

$$Action(secure\_bed(ID, sec)) \tag{A-43.a}$$
$$Pre : [rel\_homeless(A), not(A, temp\_bed(ID)), at(A, social\_worker)] \tag{A-43.b}$$
$$Add : [info(A, booked\_bed(ID))] \tag{A-43.c}$$
$$Delete : [] \tag{A-43.d}$$
)

Action 44 (Claim bed).

$$Action(claim\_bed(ID, sec)) \tag{A-44.a}$$
$$Pre : [rel\_homeless(A), not(A, temp\_bed(ID)), info(A, booked\_bed(ID)), at(A, ID)] \tag{A-44.b}$$
$$Add : [t(A, temp\_bed(ID, sec))] \tag{A-44.c}$$
$$Delete : [not(A, temp\_bed(ID)), info(A, booked\_bed(ID))] \tag{A-44.d}$$
)

Disability support

Action 45 (Receive disability support advocacy from health worker).

$$Action(receive\_disability\_support\_advocacy\_from(health\_worker, ID, sec)) \tag{A-45.a}$$
$$Pre : [t(A, disabled), not(A, disability\_support(ID, sec)), at(A, health\_worker \\ not(A, money)]), \tag{A-45.b}$$
$$Add : [info(A, disability\_support\_advocacy(health\_worker, ID, sec))] \tag{A-45.c}$$
$$Delete : [] \tag{A-45.d}$$
)

Action 46 (Receive disability support info from health worker).

$$Action(receive\_disability\_support\_info\_from(health\_worker, ID, sec)) \tag{A-46.a}$$
$$Pre : [not(A, disability\_support(ID, sec) \\ info(A, disability\_support\_advocacy(health\_worker, ID, sec)), \\ t(A, disabled), \\ at(A, health\_worker), \\ not(A, money)]), \tag{A-46.b}$$
$$Add : [info(A, disability\_support\_volunteer(ID, sec))] \tag{A-46.c}$$
$$Delete : [] \tag{A-46.d}$$
)

Action 47 (Get disability support).

$$Action(get\_disability\_support(ID, sec)) \tag{A-47.a}$$
$$Pre : [t(A, disabled), not(A, disability\_support(ID, sec) \\ info(A, disability\_support\_volunteer(ID, sec)), \\ not(A, money), \tag{A-47.b}$$

$at(A, health\_worker)]),$
$Add: [t(A, disability\_support(ID, sec))]$ (A-47.c)
$Delete: [not(A, disability\_support(ID, sec))]$ (A-47.d)
)

Action 48 (Receive disability support advocacy from health worker).

$Action(receive\_disability\_support\_advocacy\_from(health\_worker, ID, soc))$ (A-48.a)
$Pre: [t(A, disabled), not(A, disability\_support(ID, soc)), at(A, health\_worker$ (A-48.b)
$not(A, money)]),$
$Add: [info(A, disability\_support\_advocacy(health\_worker, ID, soc))]$ (A-48.c)
$Delete: []$ (A-48.d)
)

Action 49 (Receive disability support info from health worker).

$Action(receive\_disability\_support\_info\_from(health\_worker, ID, soc))$ (A-49.a)
$Pre: [not(A, disability\_support(ID, soc)$ (A-49.b)
$info(A, disability\_support\_advocacy(health\_worker, ID, soc)),$
$t(A, disabled),$
$at(A, health\_worker),$
$not(A, money)]),$
$Add: [info(A, disability\_support\_volunteer(ID, soc))]$ (A-49.c)
$Delete: []$ (A-49.d)
)

Action 50 (Get disability support).

$Action(get\_disability\_support(ID, soc))$ (A-50.a)
$Pre: [t(A, disabled), not(A, disability\_support(ID, soc)$ (A-50.b)
$info(A, disability\_support\_volunteer(ID, soc)),$
$not(A, money),$
$at(A, health\_worker)]),$
$Add: [t(A, disability\_support(ID, soc))]$ (A-50.c)
$Delete: [not(A, disability\_support(ID, soc))]$ (A-50.d)
)

Action 51 (Receive disability support advocacy from health worker).

$Action(receive\_disability\_support\_advocacy\_from(health\_worker, ID, est))$ (A-51.a)
$Pre: [t(A, disabled), not(A, disability\_support(ID, est)), at(A, health\_worker$ (A-51.b)
$not(A, money)]),$
$Add: [info(A, disability\_support\_advocacy(health\_worker, ID, est))]$ (A-51.c)
$Delete: []$ (A-51.d)
)

Action 52 (Receive disability support info from health worker).

$Action(receive\_disability\_support\_info\_from(health\_worker, ID, est))$ (A-52.a)
$Pre: [info(A, disability\_support\_advocacy(health\_worker, ID, est)$ (A-52.b)
$t(A, disabled),$
$at(A, health\_worker),$
$not(A, money)]),$
$Add: [info(A, disability\_support\_volunteer(ID, est))]$ (A-52.c)
$Delete: []$ (A-52.d)
)

Action 53 (Get disability support).

$Action(get\_disability\_support(ID, est))$ (A-53.a)
$Pre: [t(A, disabled), not(A, disability\_support(ID, est)$ (A-53.b)

$info(A, disability\_support\_volunteer(ID, est)),$
$not(A, money),$
$at(A, health\_worker)]),$
$Add : [t(A, disability\_support(ID, est))]$ (A-53.c)
$Delete : [not(A, disability\_support(ID, est))]$ (A-53.d)
)

Clean Clothing

Action 54 (Get laundry pass)**.**

$Action(get\_laundry\_pass(shelter, ID))$ (A-54.a)
$Pre : [at(A, shelter), not(A, money), t(A, laundry(ID)), not(A, laundry\_pass(ID))]$ (A-54.b)
$Add : [t(A, laundry\_pass(ID))]$ (A-54.c)
$Delete : [not(A, laundry\_pass(ID))]$ (A-54.d)
)

Action 55 (Finish laundry at shelter)**.**

$Action(finish\_laundry\_at(shelter, ID))$ (A-55.a)
$Pre : [t(A, laundry\_pass(ID)), at(A, shelter), not(A, money), t(A, laundry(ID))]$ (A-55.b)
$Add : [t(A, laundry(ID, sec)), t(A, laundry(ID, soc)), t(A, laundry(ID, est))]$ (A-55.c)
$Delete : [t(A, laundry\_pass(ID))]$ (A-55.d)
)

Action 56 (Finish laundry w money)**.**

$Action(finish\_laundry\_w\_money(laundromat, ID))$ (A-56.a)
$Pre : [at(A, laundromat), t(A, money), t(A, laundry(ID))]$ (A-56.b)
$Add : [not(A, money), t(A, laundry(ID, sec)), t(A, laundry(ID, soc)$ (A-56.c)
$t(A, laundry(ID, est))]),$
$Delete : [t(A, money)]$ (A-56.d)
)

Medication

Action 57 (Receive medication access from healthcare worker)**.**

$Action(receive\_medication\_access\_from(healthcare\_worker, M))$ (A-57.a)
$Pre : [t(A, need\_medication(M)), at(A, healthcare\_worker), not(A, money)]$ (A-57.b)
$Add : [t(A, have\_medication\_access(M))]$ (A-57.c)
$Delete : [not(A, have\_medication\_access(M))]$ (A-57.d)
)

Action 58 (Get medication from healthcare worker)**.**

$Action(get\_medication\_from(healthcare\_worker, M))$ (A-58.a)
$Pre : [t(A, need\_medication(M)), at(A, healthcare\_worker), not(A, money$ (A-58.b)
$t(A, have\_medication\_access(M))]),$
$Add : [t(A, have\_medication(M))]$ (A-58.c)
$Delete : [t(A, have\_medication\_access(M))]$ (A-58.d)
)

Action 59 (Receive medication assistance money from healthcare worker)**.**

$Action(receive\_medication\_assistance\_money\_from(healthcare\_worker, M))$ (A-59.a)
$Pre : [t(A, need\_medication(M)), at(A, healthcare\_worker), not(A, money$ (A-59.b)
$not(A, have\_medication(M))]),$
$Add : [t(A, money)]$ (A-59.c)
$Delete : [not(A, money)]$ (A-59.d)
)

Action 60 (Buy medication).

$$Action(buy\_medication(st, M)) \tag{A-60.a}$$
$$Pre : [t(A, need\_medication(M)), t(A, money), at(A, st)] \tag{A-60.b}$$
$$Add : [t(A, have\_medication(M)), not(A, money)] \tag{A-60.c}$$
$$Delete : [t(A, money)] \tag{A-60.d}$$
)

Action 61 (Take dose).

$$Action(take\_dose(M)) \tag{A-61.a}$$
$$Pre : [t(A, need\_medication(M)), t(A, have\_medication(M))] \tag{A-61.b}$$
$$Add : [not(A, need\_medication(M))] \tag{A-61.c}$$
$$Delete : [t(A, have\_medication(M)), t(A, need\_medication(M))] \tag{A-61.d}$$
)

Hygiene

Action 62 (Buy hygienic home from store).

$$Action(buy\_hygienic\_home\_from(store, ID, sec)) \tag{A-62.a}$$
$$Pre : [not(A, hygiene\_home(ID, sec)), at(A, store), t(A, money \quad t(A, have\_longterm\_housing(\_))]), \tag{A-62.b}$$
$$Add : [t(A, hygienic\_home\_product(ID, sec)), not(A, money)] \tag{A-62.c}$$
$$Delete : [t(A, money)] \tag{A-62.d}$$
)

Action 63 (Buy hygienic products from store).

$$Action(buy\_hygienic\_products\_from(store, ID, soc)) \tag{A-63.a}$$
$$Pre : [not(A, personal\_hygiene(ID, soc)), at(A, store), t(A, money)] \tag{A-63.b}$$
$$Add : [t(A, personal\_hygiene(ID, soc)), not(A, money)] \tag{A-63.c}$$
$$Delete : [not(A, personal\_hygiene(ID, soc)), t(A, money)] \tag{A-63.d}$$
)

Action 64 (Buy hygienic products from store).

$$Action(buy\_hygienic\_products\_from(store, ID, est)) \tag{A-64.a}$$
$$Pre : [not(A, personal\_hygiene(ID, est)), at(A, store), t(A, money)] \tag{A-64.b}$$
$$Add : [t(A, personal\_hygiene(ID, est)), not(A, money)] \tag{A-64.c}$$
$$Delete : [not(A, personal\_hygiene(ID, est)), t(A, money)] \tag{A-64.d}$$
)

Action 65 (Receive hygiene help from shelter).

$$Action(receive\_hygiene\_help\_from(shelter, ID, sec)) \tag{A-65.a}$$
$$Pre : [not(A, hygiene\_home(ID, sec)), at(A, shelter), not(A, money \quad t(A, have\_longterm\_housing(\_))]), \tag{A-65.b}$$
$$Add : [info(A, hygiene\_home\_referral(ID, sec))] \tag{A-65.c}$$
$$Delete : [] \tag{A-65.d}$$
)

Action 66 (Get hygiene help from charity).

$$Action(get\_hygiene\_help\_from(charity, ID, sec)) \tag{A-66.a}$$
$$Pre : [not(A, hygiene\_home(ID, sec)), info(A, hygiene\_home\_referral(ID, sec) \quad at(A, charity), \quad not(A, money), \quad t(A, have\_longterm\_housing(\_))]), \tag{A-66.b}$$
$$Add : [info(A, hygiene\_home\_volunteer(ID, sec))] \tag{A-66.c}$$
$$Delete : [info(A, hygiene\_home\_referral(ID, sec))] \tag{A-66.d}$$
)

Action 67 (Use hygiene help from charity).

$$\begin{aligned}
&Action(use_hygiene_help_from(charity, ID, sec)) && \text{(A-67.a)}\\
&\quad Pre: [not(A, hygiene_home(ID, sec)), info(A, hygiene_home_volunteer(ID, sec) && \text{(A-67.b)}\\
&\qquad at(A, home),\\
&\qquad not(A, money),\\
&\qquad t(A, have_longterm_housing(_))]),\\
&\quad Add: [t(A, hygiene_home(ID, sec))] && \text{(A-67.c)}\\
&\quad Delete: [not(A, hygiene_home(ID, sec)), info(A, hygiene_home_volunteer(ID, sec))] && \text{(A-67.d)}\\
&)
\end{aligned}$$

Action 68 (Use hygienic products from home).

$$\begin{aligned}
&Action(use_hygienic_products_from(home, ID, sec)) && \text{(A-68.a)}\\
&\quad Pre: [not(A, hygiene_home(ID, sec)), t(A, hygienic_home_product(ID, sec) && \text{(A-68.b)}\\
&\qquad at(A, home),\\
&\qquad t(A, have_longterm_housing(_))]),\\
&\quad Add: [t(A, hygiene_home(ID, sec))] && \text{(A-68.c)}\\
&\quad Delete: [t(A, hygienic_home_product(ID, sec)), not(A, hygiene_home(ID, sec))] && \text{(A-68.d)}\\
&)
\end{aligned}$$

Action 69 (Get hygienic products from shelter).

$$\begin{aligned}
&Action(get_hygienic_products_from(shelter, ID, soc)) && \text{(A-69.a)}\\
&\quad Pre: [not(A, personal_hygiene(ID, soc)), at(A, shelter), not(A, money)] && \text{(A-69.b)}\\
&\quad Add: [t(A, personal_hygiene(ID, soc))] && \text{(A-69.c)}\\
&\quad Delete: [not(A, personal_hygiene(ID, soc))] && \text{(A-69.d)}\\
&)
\end{aligned}$$

Action 70 (Get hygienic products from shelter).

$$\begin{aligned}
&Action(get_hygienic_products_from(shelter, ID, est)) && \text{(A-70.a)}\\
&\quad Pre: [not(A, personal_hygiene(ID, est)), at(A, shelter), not(A, money)] && \text{(A-70.b)}\\
&\quad Add: [t(A, personal_hygiene(ID, est))] && \text{(A-70.c)}\\
&\quad Delete: [not(A, personal_hygiene(ID, est))] && \text{(A-70.d)}\\
&)
\end{aligned}$$

Security deposit

Action 71 (Get sec deposit money).

$$\begin{aligned}
&Action(get_sec_deposit_money(housing_worker, HID)) && \text{(A-71.a)}\\
&\quad Pre: [not(A, money), at(A, housing_worker && \text{(A-71.b)}\\
&\qquad t(A, approved_for_longterm_housing(HID))]),\\
&\quad Add: [t(A, money)] && \text{(A-71.c)}\\
&\quad Delete: [not(A, money)] && \text{(A-71.d)}\\
&)
\end{aligned}$$

Action 72 (Get sec deposit advocacy).

$$\begin{aligned}
&Action(get_sec_deposit_advocacy(housing_worker, HID)) && \text{(A-72.a)}\\
&\quad Pre: [not(A, money), at(A, housing_worker && \text{(A-72.b)}\\
&\qquad t(A, approved_for_longterm_housing(HID))]),\\
&\quad Add: [info(A, sec_deposit_advocacy(HID))] && \text{(A-72.c)}\\
&\quad Delete: [] && \text{(A-72.d)}\\
&)
\end{aligned}$$

Action 73 (Get sec deposit relief).

$$\begin{aligned}
&Action(get_sec_deposit_relief(charity, HID, ID)) && \text{(A-73.a)}\\
&\quad Pre: [info(A, sec_deposit_advocacy(HID) && \text{(A-73.b)}\\
&\qquad t(A, approved_for_longterm_housing(HID)),
\end{aligned}$$

$at(A, charity)]),$

$Add : [t(A, pre\_longterm\_housing\_paid\_deposit(HID, ID))]$ (A-73.c)

$Delete : []$ (A-73.d)

)

Action 74 (Get sec deposit charity).

$Action(get\_sec\_deposit\_charity(charity, HID, ID))$ (A-74.a)

$Pre : [info(A, sec\_deposit\_advocacy(HID)$ (A-74.b)

$t(A, approved\_for\_longterm\_housing(HID)),$

$not(A, money),$

$at(A, charity)]),$

$Add : [info(A, charity\_sec\_deposit\_money(charity, ID))]$ (A-74.c)

$Delete : []$ (A-74.d)

)

Action 75 (Pay sec deposit).

$Action(pay\_sec\_deposit(money, HID, ID))$ (A-75.a)

$Pre : [t(A, money), t(A, approved\_for\_longterm\_housing(HID)), at(A, landlord)]$ (A-75.b)

$Add : [not(A, money), t(A, pre\_longterm\_housing\_paid\_deposit(HID, ID))]$ (A-75.c)

$Delete : [t(A, money)]$ (A-75.d)

)

Action 76 (Pay sec deposit).

$Action(pay\_sec\_deposit(charity, HID, ID))$ (A-76.a)

$Pre : [at(A, landlord), info(A, sec\_deposit\_advocacy(HID)$ (A-76.b)

$info(A, charity\_sec\_deposit\_money(charity, ID)),$

$t(A, approved\_longterm\_housing(HID))]),$

$Add : [t(A, pre\_longterm\_housing\_paid\_deposit(HID, ID))]$ (A-76.c)

$Delete : [info(A, sec\_deposit\_advocacy(HID)$ (A-76.d)

$info(A, charity\_sec\_deposit\_money(charity, ID))]),$

)

Action 77 (Finalize longterm housing).

$Action(finalize\_longterm\_housing(HID, ID))$ (A-77.a)

$Pre : [at(A, landlord), t(A, pre\_longterm\_housing\_paid\_deposit(HID, ID))]$ (A-77.b)

$Add : [t(A, start\_longterm\_home(HID, ID))]$ (A-77.c)

$Delete : [t(A, pre\_longterm\_housing\_paid\_deposit(HID, ID))]$ (A-77.d)

)

Addiction support

Action 78 (Get addiction pass).

$Action(get\_addiction\_pass(counselling, ID))$ (A-78.a)

$Pre : [at(A, counselling), not(A, addiction\_support(ID))]$ (A-78.b)

$Add : [t(A, pass(detox, ID))]$ (A-78.c)

$Delete : []$ (A-78.d)

)

Action 79 (Enter program).

$Action(enter\_program(detox, ID))$ (A-79.a)

$Pre : [at(A, detox), not(A, addiction\_support(ID)), t(A, pass(detox, ID))]$ (A-79.b)

$Add : [t(A, detox\_step1(ID, phys))]$ (A-79.c)

$Delete : []$ (A-79.d)

)

Action 80 (Program step1).

$$Action(program\_step1(detox, ID)) \quad \text{(A-80.a)}$$
$$Pre: [at(A, detox), not(A, addiction\_support(ID)), t(A, detox\_step1(ID, phys))] \quad \text{(A-80.b)}$$
$$Add: [t(A, detox\_step2(ID, phys))] \quad \text{(A-80.c)}$$
$$Delete: [] \quad \text{(A-80.d)}$$
)

Action 81 (Program step2).

$$Action(program\_step2(detox, ID)) \quad \text{(A-81.a)}$$
$$Pre: [at(A, detox), not(A, addiction\_support(ID)), t(A, detox\_step2(ID, phys))] \quad \text{(A-81.b)}$$
$$Add: [t(A, detox\_step3(ID, phys))] \quad \text{(A-81.c)}$$
$$Delete: [] \quad \text{(A-81.d)}$$
)

Action 82 (Program step3).

$$Action(program\_step3(detox, ID)) \quad \text{(A-82.a)}$$
$$Pre: [at(A, detox), not(A, addiction\_support(ID)), t(A, detox\_step3(ID, phys))] \quad \text{(A-82.b)}$$
$$Add: [t(A, addiction\_support(ID, phys)), t(A, detox\_step4(ID, self))] \quad \text{(A-82.c)}$$
$$Delete: [not(A, addiction\_support(ID))] \quad \text{(A-82.d)}$$
)

Action 83 (Program step4).

$$Action(program\_step4(detox, ID)) \quad \text{(A-83.a)}$$
$$Pre: [t(A, addiction\_support(ID, phys)), t(A, detox\_step4(ID, self))] \quad \text{(A-83.b)}$$
$$Add: [t(A, detox\_step5(ID, self))] \quad \text{(A-83.c)}$$
$$Delete: [] \quad \text{(A-83.d)}$$
)

Action 84 (Program step5).

$$Action(program\_step5(detox, ID)) \quad \text{(A-84.a)}$$
$$Pre: [t(A, detox\_step5(ID, self))] \quad \text{(A-84.b)}$$
$$Add: [t(A, addiction\_support(ID, self))] \quad \text{(A-84.c)}$$
$$Delete: [] \quad \text{(A-84.d)}$$
)

Transportation

Action 85 (Transit).

$$Action(transit(X, Y, sec)) \quad \text{(A-85.a)}$$
$$Pre: [at(A, X), t(A, Y, have\_token)] \quad \text{(A-85.b)}$$
$$Add: [at(A, Y), t(A, at(A, Y)), not(A, Y, have\_token), t(A, transportation(Y, sec))] \quad \text{(A-85.c)}$$
$$Delete: [at(A, X), t(A, at(A, X)), t(A, Y, have\_token)] \quad \text{(A-85.d)}$$
)

Action 86 (Transit).

$$Action(transit(X, Y, soc)) \quad \text{(A-86.a)}$$
$$Pre: [at(A, X), t(A, Y, have\_token)] \quad \text{(A-86.b)}$$
$$Add: [at(A, Y), t(A, at(A, Y)), not(A, Y, have\_token), t(A, transportation(Y, soc))] \quad \text{(A-86.c)}$$
$$Delete: [at(A, X), t(A, at(A, X)), t(A, Y, have\_token)] \quad \text{(A-86.d)}$$
)

Action 87 (Transit).

$$Action(transit(X, Y, est)) \quad \text{(A-87.a)}$$
$$Pre: [at(A, X), t(A, Y, have\_token)] \quad \text{(A-87.b)}$$
$$Add: [at(A, Y), t(A, at(A, Y)), not(A, Y, have\_token), t(A, transportation(Y, est))] \quad \text{(A-87.c)}$$

$Delete : [at(A, X), t(A, at(A, X)), t(A, Y, have\_token)]$ (A-87.d)
)

Action 88 (Request trip transit)**.**

$Action(request\_trip\_transit(social\_worker, Y))$ (A-88.a)
$Pre : [at(A, social\_worker), not(A, Y, have\_token)]$ (A-88.b)
$Add : [t(A, Y, have\_token)]$ (A-88.c)
$Delete : [not(A, Y, have\_token)]$ (A-88.d)
)

Identification

Action 89 (Get id info)**.**

$Action(get\_id\_info(case\_worker, ID, sec))$ (A-89.a)
$Pre : [at(A, case\_worker), not(A, identification(ID, sec))]$ (A-89.b)
$Add : [info(A, identification(ID, sec))]$ (A-89.c)
$Delete : []$ (A-89.d)
)

Action 90 (Use id info)**.**

$Action(use\_id\_info(id\_office, ID, sec))$ (A-90.a)
$Pre : [info(A, identification(ID, sec)), not(A, identification(ID, sec)$ (A-90.b)
$at(A, id\_office)]),$
$Add : [t(A, apply\_id\_info(ID, sec))]$ (A-90.c)
$Delete : []$ (A-90.d)
)

Action 91 (Get id)**.**

$Action(get\_id(id\_office, ID, sec))$ (A-91.a)
$Pre : [at(A, id\_office), t(A, apply\_id\_info(ID, sec)$ (A-91.b)
$not(A, identification(ID, sec))]),$
$Add : [t(A, identification(ID, sec))]$ (A-91.c)
$Delete : [not(A, identification(ID, sec))]$ (A-91.d)
)

Action 92 (Get id info)**.**

$Action(get\_id\_info(case\_worker, ID, est))$ (A-92.a)
$Pre : [at(A, case\_worker), not(A, identification(ID, est))]$ (A-92.b)
$Add : [info(A, identification(ID, est))]$ (A-92.c)
$Delete : []$ (A-92.d)
)

Action 93 (Use id info)**.**

$Action(use\_id\_info(id\_office, ID, est))$ (A-93.a)
$Pre : [info(A, identification(ID, est)), not(A, identification(ID, est)$ (A-93.b)
$at(A, id\_office)]),$
$Add : [t(A, apply\_id\_info(ID, est))]$ (A-93.c)
$Delete : []$ (A-93.d)
)

Action 94 (Get id)**.**

$Action(get\_id(id\_office, ID, est))$ (A-94.a)
$Pre : [at(A, id\_office), t(A, apply\_id\_info(ID, est)$ (A-94.b)
$not(A, identification(ID, est))]),$
$Add : [t(A, identification(ID, est))]$ (A-94.c)

$Delete : [not(A, identification(ID, est))]$ (A-94.d)
)

Child care

Action 95 (Get family serivces advocacy).

$Action(get\_family\_serivces\_advocacy(family\_services, CID, phys))$ (A-95.a)
$Pre : [not(A, child\_care(CID, phys)), not(A, money), at(A, family\_services)]$ (A-95.b)
$Add : [info(A, family\_services\_advocacy(CID, phys))]$ (A-95.c)
$Delete : []$ (A-95.d)
)

Action 96 (Get family services referral).

$Action(get\_family\_services\_referral(family\_services, CID, phys))$ (A-96.a)
$Pre : [info(A, family\_services\_advocacy(CID, phys)), not(A, money$ (A-96.b)
$at(A, family\_services)]),$
$Add : [info(A, child\_care(CID, phys))]$ (A-96.c)
$Delete : [info(A, family\_services\_advocacy(CID, phys))]$ (A-96.d)
)

Action 97 (Get family services).

$Action(get\_family\_services(charity, CID, phys))$ (A-97.a)
$Pre : [info(A, child\_care(CID, phys)), not(A, money), at(A, charity)]$ (A-97.b)
$Add : [t(A, child\_care(CID, phys))]$ (A-97.c)
$Delete : [not(A, child\_care(CID, phys)), info(A, child\_care(CID, phys))]$ (A-97.d)
)

Action 98 (Get family services).

$Action(get\_family\_services(cps, CID, phys))$ (A-98.a)
$Pre : [info(A, child\_care(CID, phys)), not(A, money), at(A, cps)]$ (A-98.b)
$Add : [t(A, child\_care(CID, phys))]$ (A-98.c)
$Delete : [not(A, child\_care(CID, phys)), info(A, child\_care(CID, phys))]$ (A-98.d)
)

Action 99 (Get family serivces advocacy).

$Action(get\_family\_serivces\_advocacy(family\_services, CID, sec))$ (A-99.a)
$Pre : [not(A, child\_care(CID, sec)), not(A, money), at(A, family\_services)]$ (A-99.b)
$Add : [info(A, family\_services\_advocacy(CID, sec))]$ (A-99.c)
$Delete : []$ (A-99.d)
)

Action 100 (Get family services referral).

$Action(get\_family\_services\_referral(family\_services, CID, sec))$ (A-100.a)
$Pre : [info(A, family\_services\_advocacy(CID, sec)), not(A, money$ (A-100.b)
$at(A, family\_services)]),$
$Add : [info(A, child\_care(CID, sec))]$ (A-100.c)
$Delete : [info(A, family\_services\_advocacy(CID, sec))]$ (A-100.d)
)

Action 101 (Get family services).

$Action(get\_family\_services(charity, CID, sec))$ (A-101.a)
$Pre : [info(A, child\_care(CID, sec)), not(A, money), at(A, charity)]$ (A-101.b)
$Add : [t(A, child\_care(CID, sec))]$ (A-101.c)
$Delete : [not(A, child\_care(CID, sec)), info(A, child\_care(CID, sec))]$ (A-101.d)
)

Action 102 (Get family serivces advocacy).

$$Action(get\_family\_serivces\_advocacy(family\_services, CID, est)) \quad \text{(A-102.a)}$$
$$Pre: [not(A, child\_care(CID, est)), not(A, money), at(A, family\_services)] \quad \text{(A-102.b)}$$
$$Add: [info(A, family\_services\_advocacy(CID, est))] \quad \text{(A-102.c)}$$
$$Delete: [] \quad \text{(A-102.d)}$$
)

Action 103 (Get family services referral).

$$Action(get\_family\_services\_referral(family\_services, CID, est)) \quad \text{(A-103.a)}$$
$$Pre: [info(A, family\_services\_advocacy(CID, est)), not(A, money \quad \text{(A-103.b)}$$
$$at(A, family\_services)]),$$
$$Add: [info(A, child\_care(CID, est))] \quad \text{(A-103.c)}$$
$$Delete: [info(A, family\_services\_advocacy(CID, est))] \quad \text{(A-103.d)}$$
)

Action 104 (Get family services).

$$Action(get\_family\_services(family\_services, CID, est)) \quad \text{(A-104.a)}$$
$$Pre: [info(A, child\_care(CID, est)), not(A, money), at(A, family\_services)] \quad \text{(A-104.b)}$$
$$Add: [t(A, child\_care(CID, est))] \quad \text{(A-104.c)}$$
$$Delete: [not(A, child\_care(CID, est)), info(A, child\_care(CID, est))] \quad \text{(A-104.d)}$$
)

Housing supplement

Action 105 (Get rent money).

$$Action(get\_rent\_money(housing\_worker, HID)) \quad \text{(A-105.a)}$$
$$Pre: [not(A, money), at(A, housing\_worker), t(A, have\_longterm\_housing(HID))] \quad \text{(A-105.b)}$$
$$Add: [t(A, money)] \quad \text{(A-105.c)}$$
$$Delete: [not(A, money)] \quad \text{(A-105.d)}$$
)

Action 106 (Get rent advocacy).

$$Action(get\_rent\_advocacy(housing\_worker, HID)) \quad \text{(A-106.a)}$$
$$Pre: [not(A, money), at(A, housing\_worker), t(A, have\_longterm\_housing(HID))] \quad \text{(A-106.b)}$$
$$Add: [info(A, rent\_advocacy(HID))] \quad \text{(A-106.c)}$$
$$Delete: [] \quad \text{(A-106.d)}$$
)

Action 107 (Get rent relief).

$$Action(get\_rent\_relief(charity, HID, ID)) \quad \text{(A-107.a)}$$
$$Pre: [info(A, rent\_advocacy(HID)), t(A, have\_longterm\_housing(HID) \quad \text{(A-107.b)}$$
$$not(A, money),$$
$$at(A, charity)]),$$
$$Add: [t(A, retain\_longterm\_home(HID, ID))] \quad \text{(A-107.c)}$$
$$Delete: [] \quad \text{(A-107.d)}$$
)

Action 108 (Get rent charity).

$$Action(get\_rent\_charity(charity, HID, ID)) \quad \text{(A-108.a)}$$
$$Pre: [info(A, rent\_advocacy(HID)), t(A, have\_longterm\_housing(HID) \quad \text{(A-108.b)}$$
$$not(A, money),$$
$$at(A, charity)]),$$
$$Add: [info(A, charity\_rent\_money(charity, ID))] \quad \text{(A-108.c)}$$
$$Delete: [] \quad \text{(A-108.d)}$$
)

Action 109 (Pay rent).

$$\begin{aligned}
&Action(pay_rent(money, HID, ID)) && \text{(A-109.a)}\\
&\quad Pre:[t(A, money), t(A, have_longterm_housing(HID))] && \text{(A-109.b)}\\
&\quad Add:[not(A, money), t(A, retain_longterm_home(HID, ID))] && \text{(A-109.c)}\\
&\quad Delete:[t(A, money)] && \text{(A-109.d)}\\
&)
\end{aligned}$$

Action 110 (Pay rent).

$$\begin{aligned}
&Action(pay_rent(charity, HID, ID)) && \text{(A-110.a)}\\
&\quad Pre:[not(A, money), info(A, rent_advocacy(HID) && \text{(A-110.b)}\\
&\qquad\quad info(A, charity_rent_money(charity, ID)),\\
&\qquad\quad t(A, have_longterm_housing(HID))]),\\
&\quad Add:[t(A, retain_longterm_home(HID, ID))] && \text{(A-110.c)}\\
&\quad Delete:[info(A, rent_advocacy(HID)), info(A, charity_rent_money(charity, ID))] && \text{(A-110.d)}\\
&)
\end{aligned}$$

Rent shortfall subsidy

Action 111 (Get rent sub money).

$$\begin{aligned}
&Action(get_rent_sub_money(housing_worker, HID, ID)) && \text{(A-111.a)}\\
&\quad Pre:[not(A, money), at(A, housing_worker), t(A, have_longterm_housing(HID) && \text{(A-111.b)}\\
&\qquad\quad not(A, rent_shortfall_subsidy(HID, ID))]),\\
&\quad Add:[t(A, money)] && \text{(A-111.c)}\\
&\quad Delete:[not(A, money)] && \text{(A-111.d)}\\
&)
\end{aligned}$$

Action 112 (Get rent sub advocacy).

$$\begin{aligned}
&Action(get_rent_sub_advocacy(housing_worker, HID, ID)) && \text{(A-112.a)}\\
&\quad Pre:[not(A, money), at(A, housing_worker), t(A, have_longterm_housing(HID) && \text{(A-112.b)}\\
&\qquad\quad not(A, rent_shortfall_subsidy(HID, ID))]),\\
&\quad Add:[info(A, rent_sub_advocacy(HID))] && \text{(A-112.c)}\\
&\quad Delete:[] && \text{(A-112.d)}\\
&)
\end{aligned}$$

Action 113 (Get rent sub relief).

$$\begin{aligned}
&Action(get_rent_sub_relief(charity, HID, ID)) && \text{(A-113.a)}\\
&\quad Pre:[info(A, rent_sub_advocacy(HID)), t(A, have_longterm_housing(HID) && \text{(A-113.b)}\\
&\qquad\quad not(A, money),\\
&\qquad\quad at(A, charity)]),\\
&\quad Add:[t(A, rent_shortfall_subsidy(HID, ID))] && \text{(A-113.c)}\\
&\quad Delete:[] && \text{(A-113.d)}\\
&)
\end{aligned}$$

Action 114 (Get rent sub charity).

$$\begin{aligned}
&Action(get_rent_sub_charity(charity, HID, ID)) && \text{(A-114.a)}\\
&\quad Pre:[info(A, rent_sub_advocacy(HID)), t(A, have_longterm_housing(HID) && \text{(A-114.b)}\\
&\qquad\quad not(A, money),\\
&\qquad\quad at(A, charity),\\
&\qquad\quad not(A, rent_shortfall_subsidy(HID, ID))]),\\
&\quad Add:[info(A, charity_rent_sub_money(charity, ID))] && \text{(A-114.c)}\\
&\quad Delete:[] && \text{(A-114.d)}\\
&)
\end{aligned}$$

Action 115 (Pay rent sub).

$$Action(pay\_rent\_sub(money, HID, ID)) \qquad \text{(A-115.a)}$$

$$Pre : [t(A, money), t(A, have\_longterm\_housing(HID) \quad \text{(A-115.b)}$$
$$not(A, rent\_shortfall\_subsidy(HID, ID))]),$$
$$Add : [not(A, money), t(A, rent\_shortfall\_subsidy(HID, ID))] \quad \text{(A-115.c)}$$
$$Delete : [t(A, money), not(A, rent\_shortfall\_subsidy(HID, ID))] \quad \text{(A-115.d)}$$
)

Action 116 (Pay rent sub)**.**

$$Action(pay\_rent\_sub(charity, HID, ID)) \quad \text{(A-116.a)}$$
$$Pre : [not(A, money), info(A, rent\_sub\_advocacy(HID) \quad \text{(A-116.b)}$$
$$info(A, charity\_rent\_sub\_money(charity, ID)),$$
$$t(A, have\_longterm\_housing(HID)),$$
$$not(A, rent\_shortfall\_subsidy(HID, ID))]),$$
$$Add : [t(A, rent\_shortfall\_subsidy(HID, ID))] \quad \text{(A-116.c)}$$
$$Delete : [info(A, rent\_sub\_advocacy(HID) \quad \text{(A-116.d)}$$
$$info(A, charity\_rent\_sub\_money(charity, ID)),$$
$$not(A, rent\_shortfall\_subsidy(HID, ID))]),$$
)

Furniture

Action 117 (Get furniture info)**.**

$$Action(get\_furniture\_info(housing\_worker, ID)) \quad \text{(A-117.a)}$$
$$Pre : [at(A, housing\_worker), not(A, money), not(A, furniture(ID) \quad \text{(A-117.b)}$$
$$t(A, have\_longterm\_housing(\_))]),$$
$$Add : [t(A, furniture\_info(furn\_bank, ID))] \quad \text{(A-117.c)}$$
$$Delete : [not(A, furniture\_info(furn\_bank, ID))] \quad \text{(A-117.d)}$$
)

Action 118 (Get furniture at furn bank)**.**

$$Action(get\_furniture\_at(furn\_bank, ID)) \quad \text{(A-118.a)}$$
$$Pre : [not(A, furniture(ID)), t(A, furniture\_info(furn\_bank, ID) \quad \text{(A-118.b)}$$
$$at(A, furn\_bank),$$
$$not(A, money),$$
$$t(A, have\_longterm\_housing(\_))]),$$
$$Add : [t(A, furniture(ID))] \quad \text{(A-118.c)}$$
$$Delete : [not(A, furniture(ID))] \quad \text{(A-118.d)}$$
)

Action 119 (Get furniture w money)**.**

$$Action(get\_furniture\_w\_money(store, ID)) \quad \text{(A-119.a)}$$
$$Pre : [at(A, store), t(A, money), not(A, furniture(ID))] \quad \text{(A-119.b)}$$
$$Add : [t(A, furniture(ID)), not(A, money)] \quad \text{(A-119.c)}$$
$$Delete : [not(A, furniture(ID)), t(A, money)] \quad \text{(A-119.d)}$$
)

Food

Action 120 (Receive food assistance from meal program)**.**

$$Action(receive\_food\_assistance\_from(meal\_program, F)) \quad \text{(A-120.a)}$$
$$Pre : [t(A, hungry(F)), at(A, meal\_program), not(A, money), not(A, have\_food(F))] \quad \text{(A-120.b)}$$
$$Add : [t(A, have\_food(F))] \quad \text{(A-120.c)}$$
$$Delete : [not(A, have\_food(F))] \quad \text{(A-120.d)}$$
)

Action 121 (Receive food assistance money from meal program)**.**

$$Action(receive\_food\_assistance\_money\_from(meal\_program, F)) \quad \text{(A-121.a)}$$

$Pre : [t(A, hungry(F)), at(A, meal\_program), not(A, money), not(A, have\_food(F))]$ (A-121.b)
$Add : [t(A, money)]$ (A-121.c)
$Delete : [not(A, money)]$ (A-121.d)
)

Action 122 (Buy food)**.**

$Action(buy\_food(store, F))$ (A-122.a)
$Pre : [t(A, hungry(F)), t(A, money), at(A, store)]$ (A-122.b)
$Add : [t(A, have\_food(F)), not(A, money)]$ (A-122.c)
$Delete : [not(A, have\_food(F)), t(A, money)]$ (A-122.d)
)

Action 123 (Eat)**.**

$Action(eat(F))$ (A-123.a)
$Pre : [t(A, hungry(F)), t(A, have\_food(F))]$ (A-123.b)
$Add : [not(A, hungry(F)), not(A, have\_food(F))]$ (A-123.c)
$Delete : [t(A, have\_food(F)), t(A, hungry(F))]$ (A-123.d)
)

Appendix D

Ontology of Social Service Needs

The complete OWL file is provided in *http://bit.ly/OSSN-Dec-8-2018-owl*.

D.1 Evaluation: Ontology of Social Service Needs

This appendix list the results for the evaluation of the OSSN. The OSSN was evaluated by constructing formal competency questions for the informal competency questions in groups 1, 2, and 3 listed in Section 6.1.6. The questions are implemented as queries in the SPARQL[1] query language. The Pellet [2] Reasoner Plug-in version 2.2.0 was used to identify and explicitly assert all class, object property, data property, and individual inferences found in OSSN. These inferences were exported into a single ontology, included in Appendix D. SPARQL Query Plugin 2.0.2 [3] was used to execute each query.

D.1.1 Group 1: Client Related Competency Questions

Q-1 What goals does client X have? For X = :chf2

```
SELECT ?goal
WHERE {
        :chf2  :hasGoal  ?goal
}
```

Table D.1: Q-1 SPARQL query results

goal
$getTempHousing2$
$getChildToysActivitiesEducationCounselling2$
$getPhoneForEmergencies2$
$getJacket2$
$getEmergencyChildCare2$
$getBasicNeedsgoodsFoodForChild2$

[1]SPARQL Query Language for RDF: *https://www.w3.org/TR/2008/REC-rdf-sparql-query-20080115/*
[2]Pellet Reasoner: *https://www.w3.org/2001/sw/wiki/Pellet*
[3]SPARQL Query Plugin 2.0.2: *https://github.com/protegeproject/sparql-query-plugin/releases/tag/sparql-query-plugin-2.0.2*

Q-2 How does client X rank their goals? Here, X = :chf2.

```
SELECT DISTINCT (STR(?index) AS ?rankindex) ?goal
WHERE {
        :chf2 :hasGoal ?goal .
        ?goal :prefAgent ?index
} ORDER BY ?index
```

Table D.2: Q-2 SPARQL query results

rankindex	**goal**
"1"	*getJacket2*
"2"	*getTempHousing2*
"3"	*getChildToysActivitiesEducationCounselling2*
"4"	*getBasicNeedsgoodsFoodForChild2*
"5"	*getEmergencyChildCare2*
"6"	*getPhoneForEmergencies2*

Q-3 What MH level needs is client X requesting? Here, X = :chf2.

```
SELECT DISTINCT ?mhneed
WHERE {
        :chf2 :hasGoal ?goal .
        ?goal :triggeredBy ?mhg .
        ?mhg :mappedTo ?mhneed .
}
```

Table D.3: Q-3 SPARQL query results

mhneed
security
esteem
physiological

Q-4 Is the practical order of goals for client X the same as MH? Here, X = :chf2.

```
SELECT ?goal (STR(?arank) AS ?agentrank) (STR(?mhrank) AS ?mhlevel)
WHERE {
        :chf2 :hasGoal ?goal .
        ?goal :prefAgent ?arank .
        ?goal :prefMH ?mhrank .

} ORDER BY ?arank ?mhrank
```

Table D.4: Q-4 SPARQL query results

goal	**agentrank**	**mhlevel**
getJacket2	"1"	"2"
getTempHousing2	"2"	"2"
getChildToysActivitiesEducationCounselling2	"3"	"4"
getBasicNeedsgoodsFoodForChild2	"4"	"2"
getEmergencyChildCare2	"5"	"1"
getPhoneForEmergencies2	"6"	"2"

Q-5 What needs are requested by clients in demographic X? Here, X = relatively homeless.

```
SELECT DISTINCT ?agent ?mhgoal
WHERE {
        ?agent rdf:type :RelHomelessAgent        .
        ?agent :hasGoal ?goal    .
        ?goal :triggeredBy ?mhgoal
} ORDER BY ?agent ?mhg
```

Table D.5: Q-5 SPARQL query results

agent	**mhgoal**
chf2	*needTempHousingShelter2*
chf2	*needHappyFamilyEsteem2*
chf2	*needPhoneStaySafe2*
chf2	*needClothing2*
chf2	*needChildBasicPhysiological2*
chf2	*needChildProtectionSecurity2*
chf3	*needToReduceStress3*
chf3	*needFurniture3*
chf3	*needPhoneSocialNetwpork3*
chf3	*needClothing3*
chf3	*needToReduceStress3x*
chf4	*needClothing4*
chf4	*needChildBasicPhysiological4*
chf4	*needHappyFamilyEsteem4*
chf4	*needPhoneStaySafe4*
chf4	*needTempHousingShelter4*

Q-6 Which clients ask for MH level X? Here, X = security MH level.

```
SELECT DISTINCT ?agent ?goal
WHERE {
        ?goal rdf:type :GoalSecurity      .
        ?agent :hasGoal ?goal             .
} ORDER BY ?agent
```

Table D.6: Q-6 SPARQL query results

agent	**goal**
$chf1$	$getSweater1$
$chf1$	$getLegalMatterResolved1$
$chf2$	$getJacket2$
$chf2$	$getBasicNeedsGoodsForChild2$
$chf2$	$getTempHousing2$
$chf2$	$getPhoneForEmergencies2$
$chf3$	$getFridge3$
$chf3$	$getPants3$
$chf3$	$getLegalMatterResolved3$
$chf3$	$getHelpResolvingCriticalIssues3$
$chf4$	$getTempHousing4$
$chf4$	$getJacket4$
$chf4$	$getPhoneForEmergencies4$

Q-7 Which demographic is asking for MH need X most? Here, X = security goals.

```
SELECT (STR(COUNT(?goal)) AS ?countg) ?demo
WHERE {
        ?goal rdf:type :GoalSecurity              .
        ?agent :hasGoal ?goal                           .
        ?agent rdf:type ?demo                           .
        ?demo rdfs:subClassOf :Demographic        .
}
GROUP BY ?demo
ORDER BY ?countg
```

Table D.7: Q-7 SPARQL query results

countg	**demo**
“12”	$RelHomeless$
“2”	$AbsHomeless$
“4”	$NotElderly$
“8”	$Elderly$

Q-8 What do clients with demographic X need most? Here, X = relatively homeless.

```
SELECT (str(COUNT(?g)) AS ?countg) ?gclass
WHERE {
        ?a rdf:type :RelHomelessAgent .
        ?a :hasGoal ?g .
        ?g rdf:type ?gclass .
        ?gclass rdfs:subClassOf :GoalMapping .
}
GROUP BY ?gclass
ORDER BY DESC(?countg)
```

Table D.8: Q-8 SPARQL query results

countg	**glcass**
"5"	*GoalChildCare*
"4"	*GoalPhone*
"3"	*GoalClothing*
"2"	*GoalTempHousing*
"2"	*GoalAddiction*
"1"	*GoalLaundry*
"1"	*GoalAdvocacyHelp*
"1"	*GoalFurniture*
"1"	*GoalAdvocacyLegal*

Q-9 Does client X ask for goals in the same order as client Y? For this query, "same goals" means the same Goal class and MH level. *GoalMapping* is used to ensure only explicitly mapped goals are used. Any inferred subclasses are not included.

```
SELECT  DISTINCT ?gchfAclass ?mhlchfA (str(?pichfA) AS ?pichfAs)
        ?mhnchfA (str(?pichfB) AS ?pichfBs) ?mhnchfB
WHERE {
        :chf2 :hasGoal ?gchfA .
        ?gchfA :prefAgent ?pichfA .
        ?gchfA rdf:type ?gchfAclass .
        ?gchfAclass rdfs:subClassOf :GoalMapping .
        ?gchfA :triggeredBy ?mhnchfA .
        ?mhnchfA :mappedTo ?mhlchfA .
        optional{
                :chf4 :hasGoal ?gchfB .
                ?gchfB :prefAgent ?pichfB .
                ?gchfB rdf:type ?gchfAclass .
                ?gchfB :triggeredBy ?mhnchfB .
                ?mhnchfB :mappedTo ?mhlchfA .
        }
} ORDER BY ASC(?pichfA)
```

Table D.9: Q-9 SPARQL query results

gchfAclass	**mhlchfA**	**pichfA**	**mhnchfA**	**pichfBs**	**mhnchfB**
GoalClothing	*security*	"1"	*needClothing*2	"1"	*needClothing*4
GoalTempHousing	*security*	"2"	*needTemp HousingShelter*2	"2"	*needTemp HousingShelter*4
GoalChildCare	*esteem*	"3"	*needHappy FamilyEsteem*2	"3"	*needHappy FamilyEsteem*4
GoalChildCare	*security*	"4"	*needChild ProtectionSecurity*2		
GoalChildCare	*physio-logical*	"5"	*needChild BasicPhysiological*2	"4"	*needChild BasicPhysiological*4
GoalPhone	*security*	"6"	*needPhone StaySafe*2	"5"	*needPhone StaySafe*4

Q-10 What motivates clients with demographic X? Here, X = relatively homeless.

```
SELECT DISTINCT ?agent ?motive
WHERE {
        ?agent rdf:type :RelHomelessAgent .
        ?motive :expressedBy ?agent .
} ORDER BY ?motive
```

Table D.10: Q-10 SPARQL query results

agent	**motive**
*chf*2	*assistanceDuringEmergency*2
*chf*4	*assistanceDuringEmergency*4
*chf*2	*beClothedForSpring*2
*chf*4	*beClothedForSpring*4
*chf*3	*haveALivableHome*3
*chf*2	*haveSociallyAdjustedKids*2
*chf*4	*haveSociallyAdjustedKids*4
*chf*3	*keepFriendsInTheLoop*3
*chf*2	*keepKidsHealthy*2
*chf*4	*keepKidsHealthy*4
*chf*3	*needSomeDressPants*3
*chf*2	*needTempHousingForShortStay*2
*chf*4	*needTempHousingForShortStay*4
*chf*2	*protectKids*2
*chf*3	*reduceStressOfOwingMoney*3
*chf*3	*resolveCriticalConflictsWithLandlord*3
*chf*3	*resolveLegalIssues*3

Q-11 What constraints clients with demographic X? Here, X = relatively homeless.

```
SELECT DISTINCT ?agent ?constraint
WHERE {
        ?agent rdf:type :RelHomelessAgent .
        ?agent :hasGoal ?goal .
        ?goal :constrainedBy ?constraint .
} ORDER BY ?constraint
```

Table D.11: Q-11 SPARQL query results

agent	constraint
$chf2$	$lackOfClothing2$
$chf3$	$lackOfClothing3$
$chf4$	$lackOfClothing4$
$chf3$	$lackOfConflictResSkills3$
$chf3$	$lackOfInfoCourageMoney3$
$chf2$	$lackOfInfoTempHousingBed2$
$chf4$	$lackOfInfoTempHousingBed4$
$chf2$	$lackOfMoney2$
$chf3$	$lackOfMoney3$
$chf3$	$lackOfMoney3x$
$chf4$	$lackOfMoney4$
$chf2$	$lackOfMoneyActivities2$
$chf4$	$lackOfMoneyActivities4$
$chf3$	$lackOfMoneyInfo3$
$chf2$	$lackOfMoneyInfo2$
$chf4$	$lackOfMoneyInfo4$

Q-12 What percentage of clients are constrained by lack of courage? The text "Courage" is used to find constraints that refer to courage.

```
SELECT (STR(?total*100/COUNT(*)) AS ?percentage)
WHERE {
        {
                SELECT (COUNT(?agent) AS ?total)
                WHERE {
                        SELECT ?agent
                        WHERE {
                                ?goal :constrainedBy ?constraint .
                                ?agent :hasGoal ?goal .
                                FILTER( regex(STR(?constraint), "Courage"))
.
                        }
                        GROUP BY ?agent
                }
        }
        ?agent rdf:type :Agent
}
GROUP BY ?total
```

Table D.12: Q-12 SPARQL query results

percentage
“50”

Q-13 Which demographic is requesting furniture?

```
SELECT ?demo
WHERE {
        ?goal rdf:type :GoalFurniture           .
        ?agent :hasGoal ?goal                     .
        ?agent rdf:type ?demo                     .
        ?demo rdfs:subClassOf :Demographic      .
}
ORDER BY ?demo
```

Table D.13: Q-13 SPARQL query results

demo
NotElderly
RelHomeless

Q-14 What percentage of relatively homeless clients and requesting furniture are not elderly?

```
SELECT (STR(?total*100/COUNT(*)) AS ?percentage)
WHERE {
        {
                SELECT (COUNT(?agent) AS ?total)
                WHERE {
                        SELECT ?agent
                        WHERE {
                                ?goal :constrainedBy ?constraint .
                                ?agent :hasGoal ?goal .
                                ?agent rdf:type :NotElderlyAgent .
                                ?goal rdf:type :GoalFurniture    .
                        }
                        GROUP BY ?agent
                }
        }
        ?agent rdf:type :RelHomelessAgent .
        ?goal rdf:type :GoalFurniture    .
}
GROUP BY ?total
```

Table D.14: Q-14 SPARQL query results

percentage
“33.333333333333333333”

Q-15 What motivates clients to use service X? Here, X = case manager.

```
SELECT DISTINCT ?motive ?service
WHERE {
        ?motive :describedMotiveFor ?goal          .
        ?goal :constrainedBy ?constraint  .
        ?resource :requiredBy ?constraint  .
        ?resource :createdBy ?service  .
        ?service rdf:type :ServiceCaseManager  .

} ORDER BY ?motive ?service
```

Table D.15: Q-15 SPARQL query results

motive	**service**
assistanceDuringEmergency2	*caseManager2*
assistanceDuringEmergency4	*caseManager4*
keepFriendsInTheLoop3	*caseManager3x*
protectKids2	*caseManager2*
reduceStressOfOwingMoney3	*caseManager3*
resolveCriticalConflictsWithLandlord3	*caseManager3*

Q-16 Are wrong conditional goals assigned to any agent, based on its demographic and MH level?

Ontology is inconsistent: assign security level "temporary housing" goal to a absolutely homeless client. It should be physiological level goal or the agent must be have a relatively homeless demographic.

D.1.2 Group 2: Service Related Competency Questions

Q-20 What client attributes are correlated with their progress in a program?

Correlation is not evaluated by the ontology. Although the information about client demogrpahics can be listed along side their outcome in a program, no inference about correlation can be inferred,

Q-21 Which types of services are aligned with which client goals?

```
SELECT DISTINCT ?sclass ?gclass
WHERE {
        ?resource :createdBy ?service    .
        ?resource :requiredBy ?constraint        .
        ?goal :constrainedBy ?constraint         .
        ?goal rdf:type ?gclass           .
        ?gclass rdfs:subClassOf :GoalMapping  .
        ?service rdf:type ?sclass                .
        ?sclass rdfs:subClassOf :ServiceMapping  .
} ORDER BY ?sclass ?gclass
```

Table D.16: Q-21 SPARQL query results

sclass	**gclass**
ServiceCaseManager	*GoalAdvocacyHelp*
ServiceCaseManager	*GoalChildCare*
ServiceCaseManager	*GoalPhone*
ServiceChildProtectiveServices	*GoalChildCare*
ServiceDonationCentre	*GoalChildCare*
ServiceDonationCentre	*GoalClothing*
ServiceDonationCentre	*GoalPhone*
ServiceFamilyServices	*GoalChildCare*
ServiceFamilyServices	*GoalClothing*
ServiceFamilyServices	*GoalPhone*
ServiceHousingWorker	*GoalFurniture*
ServiceLegalAid	*GoalAdvocacyLegal*
ServiceSocialWorker	*GoalTempHousing*

Q-22 What services can be categorized as "family services?"

```
SELECT DISTINCT ?service
WHERE {
        ?service rdf:type :ServiceFamilyServices                .
} ORDER BY ?service ?gclass ?goal
```

Table D.17: Q-22 SPARQL query results

service
*familyServices*2
*familyServices*4

Q-23 What services are needed together to address "child care goals"?

```
SELECT DISTINCT ?service ?sclass
WHERE {
        ?resource :createdBy ?service   .
        ?resource :requiredBy ?constraint       .
        ?goal :constrainedBy ?constraint        .
        ?goal rdf:type :GoalChildCare           .
        ?service rdf:type ?sclass               .
        ?sclass rdfs:subClassOf :ServiceMapping         .
} ORDER BY ?service ?gclass ?goal
```

Table D.18: Q-23 SPARQL query results

service	**sclass**
caseManager2	*ServiceCaseManager*
childProtectiveServices2	*ServiceChildProtectiveServices*
childProtectiveServices4	*ServiceChildProtectiveServices*
donationCentre2	*ServiceDonationCentre*
donationCentre4	*ServiceDonationCentre*
familyServices2	*ServiceFamilyServices*
familyServices4	*ServiceFamilyServices*

Q-24 What resources are needed to address a client's "child care goals"?

```
SELECT DISTINCT ?resource
WHERE {
        ?resource :createdBy ?service .
        ?resource :requiredBy ?constraint .
        ?goal :constrainedBy ?constraint .
        ?goal rdf:type :GoalChildCare .
} ORDER BY ?resource
```

Table D.19: Q-24 SPARQL query results

resource
resourceCaseManager2
resourceCharity2
resourceCharity4
resourceHolidayPresents2
resourceHolidayPresents4
resourceSocialWorker2
resourceSocialWorker4
resourceAdvocacy2
resourceAdvocacy4

Q-25 What resources and services are needed to address a client's security-level needs?

```
SELECT DISTINCT ?service ?resource
WHERE {
        ?resource :createdBy ?service .
        ?resource :requiredBy ?constraint .
        ?goal :constrainedBy ?constraint .
        ?goal :triggeredBy ?mhgoal .
        ?mhgoal rdf:type :MHGoalSecurity .
} ORDER BY ?resource
```

Table D.20: Q-25 SPARQL query results

service	**resource**
caseManager2	*resourceCaseManager2*
caseManager3	*resourceCaseManager3*
caseManager4	*resourceCaseManager4*
donationCentre1	*resourceCharity1*
donationCentre2	*resourceCharity2*
familyServices2	*resourceCharity2*
donationCentre3	*resourceCharity3*
donationCentre4	*resourceCharity4*
housingWorker3	*resourceInfo3*
legalAid1	*resourceLegalWorker1*
legalAid3	*resourceLegalWorker3*
housingWorker3	*resourceMoney3*
socialWorker2	*resourceTempBed2*
socialWorker4	*resourceTempBed4*

Q-26 How well do programs address physiological and security needs of clients?

```
SELECT DISTINCT (STR(COUNT(*)) AS ?count) ?program ?outcome_flag ?mhneed
WHERE {
        ?service :accessedBy ?agent .
        ?program :offers ?service .
        ?outcome :forProgram ?program .
        ?agent :hasOutcome ?outcome .
        ?agent :hasGoal ?goal .
        ?goal :constrainedBy ?constraint .
        ?resource :requiredBy ?constraint .
        ?resource :createdBy ?service .
        ?goal :triggeredBy ?mhgoal .
        ?mhgoal :mappedTo ?mhneed
        {
            { ?mhgoal rdf:type :MHGoalPhysiological }
              UNION
            {?mhgoal rdf:type :MHGoalSecurity}} .
        {
            {?outcome rdf:type :OutcomeSuccess . BIND("succ" AS ?outcome_flag) }
              UNION
            {?outcome rdf:type :OutcomeFail . BIND("fail" AS ?outcome_flag) }
              UNION
            {?outcome rdf:type :OutcomeMissing . BIND("miss" AS ?outcome_flag) }
        }
} GROUP BY ?program ?mhneed ?outcome_flag
ORDER BY ?program ?count ?mhneed ?outcome_flag
```

Table D.21: Q-26 SPARQL query results

count	**program**	**outcome_flag**	**mhneed**
"1"	*program*1	"fail"	*physiological*
"1"	*program*1	"succ"	*physiological*
"1"	*program*1	"fail"	*security*
"4"	*program*1	"succ"	*security*
"1"	*program*2	"fail"	*physiological*
"1"	*program*2	"succ"	*physiological*
"5"	*program*2	"fail"	*security*
"1"	*program*3	"fail"	*security*
"1"	*program*3	"succ"	*security*
"2"	*program*4	"succ"	*security*

Q-27 Are resources available when needed?

The rate at which resources are used or when they become unavailable is not captured by the ontology. While an extension to the *Resource* object can be made that captures inventory and availability, the temporal dimension required to capture changes in either metric is not available.

Q-28 How did other pilot projects perform in delivering a comparable service?

Other pilot project were not included in the CHF-HF dataset. If they were, program outcomes for similar clients could be captured for services based on the same *Service* class.

Q-29 When should a program intervene in a client's progress?

Since the temporal dimension is not included in the ontology, the timing of program intervention is not supported.

D.1.3 Group 3: Process related questions

The questions in group 3 relate to the process of decision making. They evaluate the ontologies ability to identify patterns in the data and casual relationships between entities. OSSN was not designed to make such inferences. While relations between entities are captured, they are limited to static definitions. An evaluation of the process of decision making is outside the scope of OSSN. Question Q-30 ("What interim goals are required to satisfy goal X?") can be answered by generating a plan using the action schema *AS* and STRIPS-BR planner. However, evaluation of the planner is outside the scope of this chapter. The remaining questions, Q-31 to Q-37, require either a simulated execution of a plan to evaluate replanning, or inquire about the emotional changes that occur during plan execution. Such analysis is addressed in Chapter 7.

Appendix E

Experiment Reports

The experiment evaluated in Chapter 7 was the last in a series of five experiments conducted using the CHF-HF dataset[1]. The four previous experiments incrementally investigated the limits of what can be predicted about clients whose behaviour seems "irrational." This appendix contains the entire experiment reports for Experiments 1 to 5.

The initial evaluation of CHF-HF data is described in Appendix A. All experiments rely on factorial-experiment design, as described by Barton [16]. Various methods and configurations are used to find the best performing model.

[1]Please note, the analysis and findings reported in this thesis based on the Calgary Homeless Foundation's Housing First dataset (CHF-HF) do not reflect the views of the Foundation.

E.1 Experiment 1: CHF Participant Predictions At Baseline

E.1.1 Introduction

This experiment report is a comparison of the analysis performed by [257], where predictive analysis was performed on the At Home/Chez Soi (AH-CS) Housing First intervention program. The objective of the AH-CS analysis was to determine whether client characteristics at intake can be used to predict successful exit from the program. Full description of the program can be found at [95]. The analysis presented in this report applies similar analysis to the Housing First program administered by the Calgary Homeless Foundation (CHF-HF), and described in Appendix A.

Hypothesis: A seemingly "irrational" client's probability of success can be predicted by considering their demographics at program intake.

In [257], the main question asked was: "Can we predict, at admission, the characteristics of individuals who will continue to experience housing instability after one year in the HF program?" This experiment report asks the same question about the CHF-HF study, but with five key differences in the methodology and administration between each program. First, the AH-CS program was administered across five Canadian cities, while CHF-HF was administered by multiple sites within Calgary, Canada. Second, the AH-CS included a HF cohort and a treatment as usual (TAU) control group. In CHF-HF, no control group was available and all participants were included in the HF program. Third, AH-CS excluded participants not absolutely homeless or relatively homeless with some

Third, AH-CS focused on individuals who have some form of psychiatric diagnosis, with non-diagnosed individuals excluded from the study. CHF-HF included everyone who met the acuity level requirement. Finally, participants with moderate and high level of psychiatric needs were assisted using two different models of assistance. Participants in the CHF-HF study were assisted by models chosen by the individual site in the program according to resources and needs indicated by the clients at various intervals.

Unfortunately, both studies produced weak models, with prediction accuracy improvements of only 3.8% and 4.8% over random selection for AH-CS and CHF-HF respectively. The conclusion of both experiments was that relying only on data at intake is insufficient to predict client outcomes in the Housing First intervention program. A study by Adair et al. evaluated the AH-CS dataset by identifying latent trajectories for different classes of participant demographics [2]. This study incorporated longitudinal data to predict client outcomes. Similar approach will be incorporated in followup experiments presented here.

Background

Details of the CHF-HF and AH-CS programs can be found at [89] and [95] respectively. Details of the analysis on the AH-CS program can be found in [257]. Both programs are based on the "Pathways to Homelessness" program developed by [247]. Both the At Home/Chez Soi and "Pathways to Homeless" programs target people with mental illness and addiction. The CHF program applies to all people who experience homelessness living in the Calgary area [89].

CHF-HF has four key principles developed by the Canadian Alliance to End Homelessness:

1. consumer choice and self-determination;

2. immediate access to permanent housing with the support necessary to sustain it;

3. housing is not conditional on sobriety or program participation;
4. social inclusion, self-sufficiency and improved quality of life and health.

Participant Selection and Data Collection Methods

The participants selection process and pool of participants differed between the two studies, as described in Table E.1.1.

Table E.1: Participant selection criteria comparison between AH-CS and CHF-HF

AH-CS Criteria	**CHF-HF Criteria**
Scope: 5 cities across Canada.	Anyone eligible for the program living in Calgary, Canada.
Stably housed: 6 months of retrospective housing data, housed more than 50% of the time in last 9 months, 100% housed for at least 3 months of first year a success Housed less than 50%	Stably housed: Did not exit to "Staying with family or friends (couch surfing)" or "Outside (rough sleeping, camping, vehicle)"
Success: Stably housed within a year Have legal status as Canadian Citizen, landed immigrant, or refugee	Success: Stably housed within a year Canadian Citizen, Permanent Resident (Landed Immigrant), Refugee Claimant,Refugee Permanent Resident
Having legal adult status	non-Youth: Sector = Family or Single
Being absolutely homeless OR precariously housed with two or more episodes of absolute homelessness in past year	Absolutely homeless OR total homeless months >= 1 (including chronically and episodically).
Have a psychiatric diagnosis	Has some form of known mental problem, treated, untreated, and both.
Excluded if spent < 66% in institution of the first year in program	Excluded if spent < 180 days in the last 9 months (66%) of the first year in an institution; hospital or jail
Excluded anyone currently receiving ACT or ICM support	not applicable

Data was collected through in-person interviews administered by practitioners or program administrators. The CHF-HF data was captured across 50 sites in the Calgary area. The AH-CS study was conducted at sites across five Canadian cities. Client needs were met according to their level of psychiatric need. Specifically, High-need individuals were split into assertive community treatment (ACT) and treatment as usual (TAU), while participants with moderate needs were split into intensive case management (ICM) and TAU groups.

The CHF-HF program did not focus on clients with mental illness. The low success rate in the portion of participants reflects this difference. All individuals participated in the Housing First option, hence no TAU group was tracked separately.

Both are longitudinal studies, and involve follow up meetings with participants at three month intervals until exiting the program where each questionnaire was administered.

Table E.2: Participant breakdown comparison between AH-CS and CHF-HF

Characteristic	**AH-CS Criteria**	**CHF-HF Criteria**
Assessed for eligibility (count)	HF = 2,866 / TAU = 990	HF = 2,255 / TAU = 0
Participants	1,265	1,076
Stably housed	1005 (78%)	704 (38%)
Male	775 (66%)	1022 (55%)
Average Age	41	42
Aboriginal	261 (22%)	449 (24%)
Ethnoracial	276 (23%)	193 (10%)

E.1.2 Experiment Design

This experiment uses the factorial-experiment design described by Barton [16]. The variables and metrics used are based on Volk et al., but rely on additional classification models [257], as listed in the Method section. The prediction results are compared to random guesses.

Materials

Each program used different questionnaire to capture data. The AH-CS used the "Residential Time-Line Follow-Back Inventory" (RTLFB) questionnaire, while CHF-HF used the HF Assessment questionnaire. RTLFB focuses on longitudinal studies and their comparison. It proved a "reliable method for measuring the key outcome variables in this large-scale multi-site study of homelessness and residential stability among individuals with psychiatric disabilities and/or substance use disorders" [248]. HF Assessment focuses on how best to provide for client needs in housing programs. It does not focus on any specific group of people. It does not focus on people who are especially suitable for permanent housing. Both methods have the capacity to capture patterns of change over an extended period of time. This provides a sufficient mechanism for capturing variability in an individual's in homelessness and residential patterns.

Variables

Independent Variables:

- Client demographics, as per Table E.3.

Dependent Variables:

- Success state of a client, where Success $\in$ [Yes, No].

Output Variables:

- Precision score of a supervised learning classifier.

Table E.3: Client Demographics considered.

Demographics	N
MentalFacil-k : Spent time in a mental facility in the pst 12 months.	
No	972
Yes	123
Unknown	7
Gender-k : Client's gender.	
Male	594
Female	506
Transgender	2
PhysProb-k : Whether they live with any physical issues.	
Yes	643
No	459
Employed-k : Client's employment state.	
No	523
No - Unable to work	353
F/T	118
P/T	102
Unknown	5
Declined to answer	1
InstitutionalizedDays-k : Number of days spent institutionalized.	
-0.0	548
0.0-66.0	449
66.0-132.0	51
132.0-198.0	23
198.0-264.0	16
264.0-330.0	11
330.0-396.0	4
HealthFacil-k : Came into the program from a health facility.	
No	787
Yes	303
Unknown	12
PrimRes-k : The client's primary residence before joining the program.	
Emergency shelter	442
Couch	200
Addiction Facility	106
Rough	103
Rent/Short-Term	87
Institution	70
Rent/Long-Term	61
Other	25
Dwelling unfit for human habitation	6
Unknown	1
CIS	1
FamilySitu-k : Family status.	

Demographics	N
Single	808
Single w Family	191
Couple w Family	50
Couple	39
Unknown	14
MentalProb-k : Experiences from Mental issues.	
Yes	577
No	525
GAge-k : Age range.	
36-50	385
51+	286
25-35	270
0-24	161
Sector-k : Family sector.	
Single	769
Family	249
Youth	84
CIC-k : Citizenship status.	
Canadian Citizen	1029
Permanent Resident (Landed Immigrant)	61
Refugee - Permanent Resident	7
Refugee - Claimant	5
UempDur-k :Duration of unemployment.	
More than 3 years	282
0	235
1 to 3 years	221
6 to 12 months	167
1 month or less	34
3 months	32
5 months	31
4 months	25
2 months	23
Don't know	21
Unknown	16
Declined to answer	15
AbsRel-k : Whether client is absolutely or episodically homeless.	
Absolute	727
Relative	375
EmpAbility-k : Whether the client is able to hold employment.	
No	582
Yes	486
Unknown	34
Addict-k : Whether the client suffers from addiction, treated or otherwise.	
Yes	635
No	467

Method

Classification predictions were performed using six different classifiers:

LogReg: Logistical regression [2].

SVM: Support vector machines [3].

KNN: k-nearest neighbour [4].

NaiveBayes: Naive Bayes classifier with gaussian distribution [5].

Tree Regr: 1-dimensional decision tree regression [6].

RandomTreeRegr: Random forest regressor [7].

[2] Logistical regression: *http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html*.

[3] Support vector machines: *http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html*.

[4] k-nearest neighbour: *http://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html*.

[5] Naive Bayes: *http://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.GaussianNB.html*.

[6] Decision Tree regression: *http://scikit-learn.org/stable/auto_examples/tree/plot_tree_regression.html*.

[7] Random forest regressor: *http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html*.

E.1.3 Results

Table E.4: Prediction results using characteristics where $p \leq 0.05$ for each classifier

Characteristic	χ^2	N	P(LogReg) - P(random)	P(SVM) - P(random)	P(KNN) - P(random)	P(NaiveBayes) - P(random)	R^2(Tree Regr)	R^2(Random Tree Regr)
All where $p \leq 0.05$	-	-	0.002	-0.004	-0.014	0.015	-0.128	0.258
Have addiction - Both Treated and Untreated, *	4.1	149	0.048	0.048	0.048	0.048	-0.029	-0.033
Served in Canadian Forces? Don't Know, **	7.9	2	-0.004	-0.001	-0.004	-0.001	0.012	0.013
Require disability accommodations? Don't Know, ***	11.2	5	0.005	0.009	0.009	0.009	0.012	0.012
Education? Don't Know, **	7.9	2	-0.034	-0.034	-0.034	-0.034	-0.014	-0.015
Are you employed?								
No - Unable to work, *	4.8	433	0.019	0.019	0.019	0.019	-0.007	-0.008
No, *	4.9	468	-0.008	-0.008	-0.304	-0.008	-0.021	-0.027
If unemployed, for how many months?								
Don't know, **	7.7	17	-0.011	-0.011	-0.011	-0.011	0.005	0.002
More than 3 years, *	5.4	330	0.009	0.009	-0.399	0.009	-0.01	-0.011
In Foster care system? Don't Know, ***	11.5	17	0.009	0.009	0.009	0.009	-0.011	-0.016
In healthcare system? Don't Know, **	7.5	4	0.032	0.035	0.032	0.035	-0.002	-0.003
Healthcare system								
No. of emergency room visits? 0, **	10.8	3.1	-0.001	-0.001	-0.001	-0.018	-0.022	-0.031
No. of emergency medical services visits? (0), ***	15	1.6	0.002	-0.004	-0.011	-0.014	0.006	0.013
Days in hospital? 0, *	5.2	14.8	0.005	0.005	-0.004	0.005	-0.045	-0.023
Days in jail? 0, *	5.7	11.8	0.009	0.009	0.012	0.009	-0.04	-0.042
First language?								
English, **	9.1	944	0.038	0.038	0.038	0.038	-0.007	0
Other, **	7.7	54	-0.004	-0.004	-0.004	-0.004	0.011	0.012
Living with mental problems?								
Yes - Treated, ***	17.5	409	-0.014	-0.014	-0.176	-0.014	0.027	0.024
Yes - Untreated, **	9.1	309	0.009	0.009	0.009	0.009	-0.002	-0.002
Living with physical problems?								
Yes - Both Treated and Untreated, *	4.4	260	-0.014	-0.014	-0.014	-0.014	0.005	0.005
Yes - Both Treated and Untreated, *	4.4	260	-0.014	-0.014	-0.014	-0.014	0.005	0.005
Immigration status? Recent Immigrant and New to Province, *	4	3	-0.004	-0.004	-0.004	-0.004	-0.007	-0.002

Table E.4: Prediction results using characteristics where $p \leq 0.05$ for each classifier

Characteristic	χ^2	N	P(LogReg) - P(random)	P(SVM) - P(random)	P(KNN) - P(random)	P(NaiveBayes) - P(random)	R^2(Tree Regr)	R^2(Random Tree Regr)
What was your primary residence prior to the program?								
Couch surfing, *	3.9	1	-0.014	-0.014	-0.014	-0.014	-0.003	-0.002
Emergency shelter, *	6.5	381	0.002	0.002	-0.245	0.002	-0.001	0
Hospital/medical facility, ***	11.5	52	-0.018	-0.018	-0.018	-0.514	0.007	0.006
Long-term housing with supports, *	4.9	5	0.025	0.025	0.025	0.028	0	-0.003
Staying with family or friends (couch surfing), *	4.6	191	-0.031	-0.031	-0.031	-0.031	-0.004	-0.008
Residential Addiction Facility?								
Declined to Answer, *	3.9	1	0.005	0.005	0.005	0.005	0	-0.001
Family status								
Head of household, *	3.9	166	-0.021	-0.021	-0.021	-0.021	-0.007	-0.005
Single, *	3.9	845	0.009	0.009	0.009	0.009	-0.005	-0.007
No. of Dependents? 0, *	5.4	0.5	-0.027	-0.027	-0.027	-0.027	0.035	0.032
Have you been released from an institution in past 12 months?								
HealthFacility: Don't Know, **	7.9	2	0.019	0.019	0.019	0.019	-0.004	-0.003

Table E.5: Prediction results using characteristics where $p \leq 0.05$ and $N > 100$ for each classifier

Characteristic	χ^2	N	P(LogReg) - P(random)	P(SVM) - P(random)	P(KNN) - P(random)	P(NaiveBayes) - P(random)	R^2(Tree Regr)	R^2(Random Tree Regr)
All where $p \leq 0.05$	-	-	0.002	-0.004	-0.014	0.015	-0.128	0.258
Have addiction - Both Treated and Untreated, *	4.1	149	0.048	0.048	0.048	0.048	-0.029	-0.033
Are you employed?								
No - Unable to work, *	4.8	433	0.019	0.019	0.019	0.019	-0.007	-0.008
No, *	4.9	468	-0.008	-0.008	-0.304	-0.008	-0.021	-0.027
If unemployed, for how many months?								
Don't know, **	7.7	17	-0.011	-0.011	-0.011	-0.011	0.005	0.002
More than 3 years, *	5.4	330	0.009	0.009	-0.399	0.009	-0.01	-0.011
In Foster care system? Don't Know, ***	11.5	17	0.009	0.009	0.009	0.009	-0.011	-0.016

Table E.5: Prediction results using characteristics where $p \leq 0.05$ and $N > 100$ for each classifier

Characteristic	χ^2	N	P(LogReg) - P(random)	P(SVM) - P(random)	P(KNN) - P(random)	P(NaiveBayes) - P(random)	R^2(Tree Regr)	R^2(Random Tree Regr)
First language?								
English, **	9.1	944	0.038	0.038	0.038	0.038	-0.007	0
Other, **	7.7	54	-0.004	-0.004	-0.004	-0.004	0.011	0.012
Living with mental problems?								
Yes - Treated, ***	17.5	409	-0.014	-0.014	-0.176	-0.014	0.027	0.024
Yes - Untreated, **	9.1	309	0.009	0.009	0.009	0.009	-0.002	-0.002
Living with physical problems?								
Yes - Both Treated and Untreated, *	4.4	260	-0.014	-0.014	-0.014	-0.014	0.005	0.005
Yes - Both Treated and Untreated, *	4.4	260	-0.014	-0.014	-0.014	-0.014	0.005	0.005
What was your primary residence prior to the program?								
Couch surfing, *	3.9	1	-0.014	-0.014	-0.014	-0.014	-0.003	-0.002
Emergency shelter, *	6.5	381	0.002	0.002	-0.245	0.002	-0.001	0
Hospital/medical facility, ***	11.5	52	-0.018	-0.018	-0.018	-0.514	0.007	0.006
Long-term housing with supports, *	4.9	5	0.025	0.025	0.025	0.028	0	-0.003
Staying with family or friends (couch surfing), *	4.6	191	-0.031	-0.031	-0.031	-0.031	-0.004	-0.008
Family status								
Head of household, *	3.9	166	-0.021	-0.021	-0.021	-0.021	-0.007	-0.005
Single, *	3.9	845	0.009	0.009	0.009	0.009	-0.005	-0.007
No. of Dependents? 0, *	5.4	0.5	-0.027	-0.027	-0.027	-0.027	0.035	0.032

E.1.4 Analysis and Discussion

In both the AH-CS and CHF-HF studies, a small amount of missing data was imputed at the level of individual items using expectation maximization, 3.8% for AH-CS, and 2.1% for CHF-HF. Table A.1 contains prediction results based on individual attributes for which $p \leq 0.05$. The complete list of attributes and their p values provided by Table A.1 in Appendix A. Each classifier only had minor improvements in accuracy over guessing "success" vs "unsuccessful" at random, where $P(x)$ is the accuracy of method x. Whether the client had treated and untreated mental problems saw an improvement of 4.8%. An improvement for 3.8% of clients was observed based on the first language being English.

E.2 Experiment 2: Predict exit status using demographics and MH levels

E.2.1 Introduction

This report is an update on the model from Experiment 1 in Appendix E.1 created to predict client outcomes in the Calgary Homeless Foundation Housing First dataset (CHF-HF) using client demographics at intake. The purpose of this experiment is to find a model that also includes client needs to predict whether a participant will exit the program successfully or unsuccessfully within the first 12 months. This experiment categorizes client needs using Maslow hierarchy to improve models predicting client success in the CHF-HF intervention program. Similarly to Adair et al. [2], this experiment incorporated longitudinal information. Adair et al. relied on growth mixture modelling [168, 199] to identify classes of participants based on statistically derived patterns of latent variables to predict program outcomes. The experiment presented here relies on a support vector machine using trajectory of changing needs to predict program outcomes.

Hypothesis: A seemingly "irrational" client's probability of success can be predicted by considering their number of needs in each level of Maslow's hierarchy.

A comparison is performed against similar methods in Experiment 1. Based on this comparison we see that tracking changes in client needs may help in predicting client outcomes in an intervention program. While the improvements were not significant, the average predictive score was higher for variables capturing changing needs and client behaviour, indicating that some attributes of clients may be more indicative of outcome than others. Adair et al. also concluded that, while no explicit predictor was found, some classes of trajectories were dominated by certain demographics, highlighting a potential correlation [2]. However, no prediction about outcome for particular individuals could be made.

E.2.2 Experiment Design

Method

The classification algorithm chosen is an SVM algorithm [8] with the "radial basis function" kernel. Other classifiers were used but this classifier consistently had best results.

Variables

Independent Variables:

- Client demographics, as per Table E.6.
- Needs mapped to Maslow's hierarchy.
- Number of needs at each level of Maslow's hierarchy (MH), for each three-month interval.

Dependent Variables:

- Success state of a client, where Success $\in$ [Yes, No].

Output Variables:

- Precision score of a supervised learning classifier.

[8]SKLearn SVM Algorithm: *http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html*

Table E.6: Client Demographics considered.

Demographics	**N**
MentalFacil-k : Spent time in a mental facility in the pst 12 months.	
No	972
Yes	123
Unknown	7
Gender-k : Client's gender.	
Male	594
Female	506
Transgender	2
PhysProb-k : Whether they live with any physical issues.	
Yes	643
No	459
Employed-k : Client's employment state.	
No	523
No - Unable to work	353
F/T	118
P/T	102
Unknown	5
Declined to answer	1
InstitutionalizedDays-k : Number of days spent institutionalized.	
-0.0	548
0.0-66.0	449
66.0-132.0	51
132.0-198.0	23
198.0-264.0	16
264.0-330.0	11
330.0-396.0	4
HealthFacil-k : Came into the program from a health facility.	
No	787
Yes	303
Unknown	12
PrimRes-k : The client's primary residence before joining the program.	
Emergency shelter	442
Couch	200
Addiction Facility	106
Rough	103
Rent/Short-Term	87
Institution	70
Rent/Long-Term	61
Other	25
Dwelling unfit for human habitation	6
Unknown	1
CIS	1
FamilySitu-k : Family status.	
Demographics	**N**
Single	808
Single w Family	191
Couple w Family	50
Couple	39
Unknown	14
MentalProb-k : Experiences from Mental issues.	
Yes	577
No	525
GAge-k : Age range.	
36-50	385
51+	286
25-35	270
0-24	161
Sector-k : Family sector.	
Single	769
Family	249
Youth	84
CIC-k : Citizenship status.	
Canadian Citizen	1029
Permanent Resident (Landed Immigrant)	61
Refugee - Permanent Resident	7
Refugee - Claimant	5
UempDur-k :Duration of unemployment.	
More than 3 years	282
0	235
1 to 3 years	221
6 to 12 months	167
1 month or less	34
3 months	32
5 months	31
4 months	25
2 months	23
Don't know	21
Unknown	16
Declined to answer	15
AbsRel-k : Whether client is absolutely or episodically homeless.	
Absolute	727
Relative	375
EmpAbility-k : Whether the client is able to hold employment.	
No	582
Yes	486
Unknown	34
Addict-k : Whether the client suffers from addiction, treated or otherwise.	
Yes	635
No	467

E.2.3 Results

The results in Figure E.1 show top predictions for demographics only (demo=X where X is one of the attributes in Table 1), and MH with and without demographics. For MH results (Maslow Count), only results for bottom four levels (0-4) of MH were included in this graph as they had the best results overall.

Top two demographics (demo=top-2) include the participant's employment (Employment-k) status and length of time spent at a "mental facility" (MentalFacil-k) before starting the program. Key three demographics (demo=key-3) include the participant's age (GAge-k), whether they suffer from mental health issues (MentalProb-k), and whether they are absolutely or relatively homeless (AbsRel-k). When including the number of needs for each level of MH, there is an increase of 3% over the top results for top two demographics (demo=top-2).

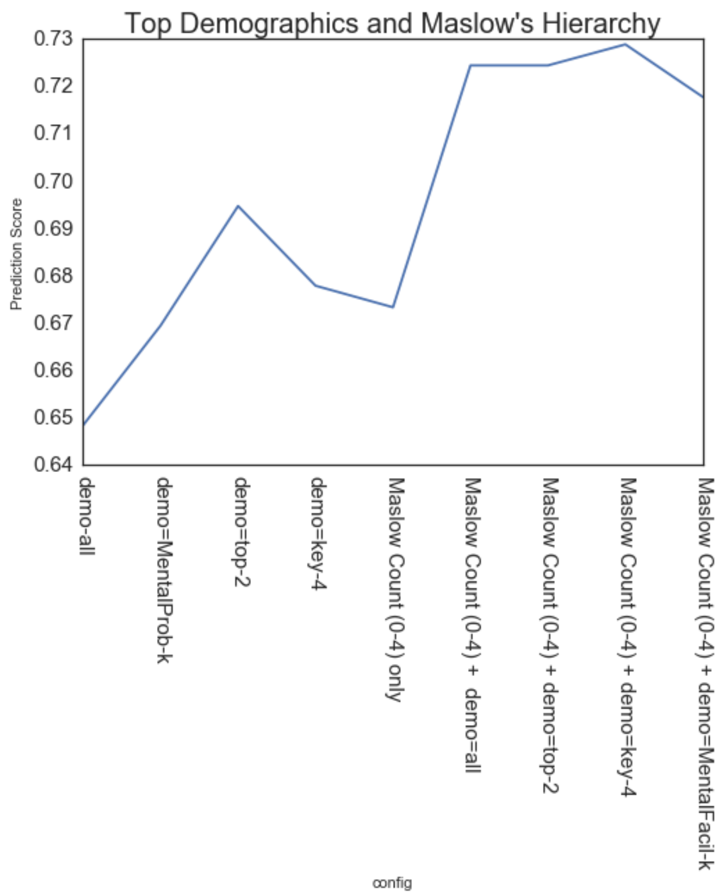


Figure E.1: Prediction based on count of needs in first four levels of Maslow's hierarchy compared to Demographics

E.2.4 Analysis and Discussion

The increase in predictive power of MH needs is not as high as was expected. It should be noted that precision of predictions that rely only on the number of needs in each level of MH performed as good, and on average better than without MH, with a 67% precision rate. This shows that only relying on MH is sufficient to predict client outcomes when compared to demographics and other client characteristics.

One of the causes for low results in [257] was the overfitting that occurred, successfully predicting only 3.8% of clients. The model developed here suffers from similar results although it has a higher rate of success.

E.3 Experiment 3: Predict exit status using demographics, MH levels, and ECOC stages

E.3.1 Introduction

This report is an update on the model from Experiment 2 in Appendix E.2 created to predict client outcomes in the Calgary Homeless Foundation Housing First dataset (CHF-HF).

The purpose of this experiment is to find a model based on client needs and emotional state that can predict whether a participant will exit the program successfully or unsuccessfully within a year. This experiment extends the classification of client needs by identifying a client's stage in the Emotional Cycle Of Change (ECOC). The stages are used to predict client outcomes in the CHF-HF intervention program. A state machine is used to transition the agent from one ECOC stage to another. The transitions are based on MH levels captured by the CHF data.

Hypothesis: A seemingly "irrational" client's probability of success can be predicted by relying on a client's ECOC stages in the CHF-HF program.

The results of the experiment presented show that tracking changes in client needs can help in predicting client outcomes in an intervention program. While the improvements were not significant, the average predictive score was higher for variables capturing changing needs and client behaviour. Most notably, ECOC stages alone had the same and more often higher predictive scores than those based on traditional demographics, albeit not by a great margin. However, early analysis shows that the methods presented in Experiment 3 based on ECOC stages are less prone to overfitting, hence are more robust than predictive models based on static client demographics.

As a client participates in a program, the goal is to increase their chances of success. The program hopes to provide the client with resources required to exit homelessness successfully and change their behaviour in a way that leads to success. For this experiment, changes in client behaviour were tracked by capturing the changes in the number of needs per MH level, at each three-month period. The changes in needs were used to derive a client's ECOC stage at each period. A client's trajectory through the ECOC stages in the program was simulated based on the number of needs they requested at each period.

E.3.2 Experiment Design

Method

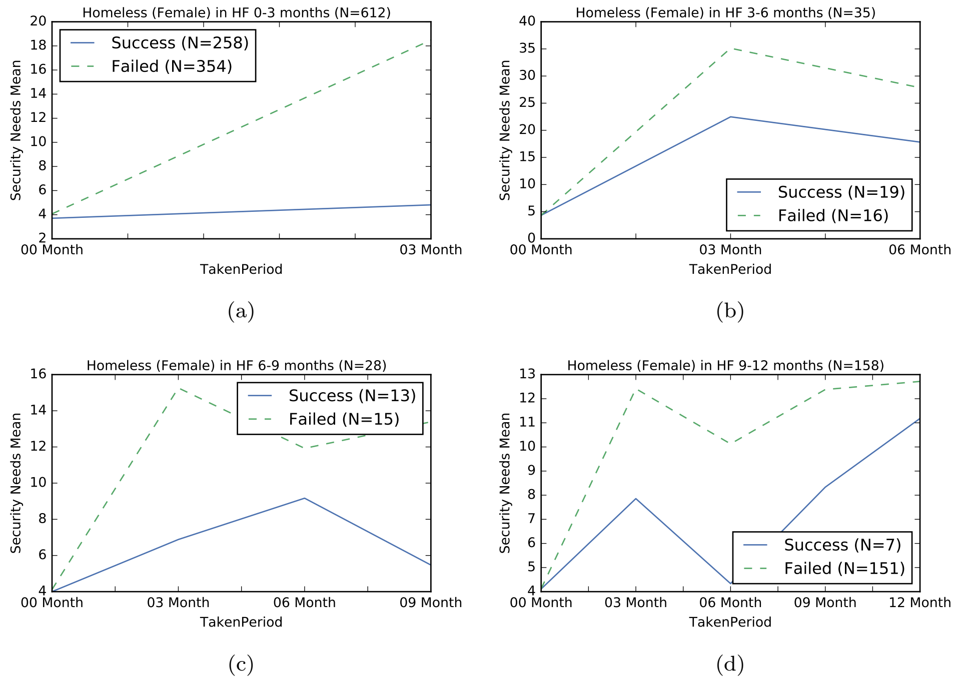
Transitions of a client's ECOC stages depend on the number of needs in each of Maslow's levels. The methods in this experiment rely on ECOC stage initialization rules (Algorithm 1) and ECOC state transition table (Table E.8). These were derived from analysis of graphs similar to Figures E.2 (a to d). These graphs indicate how the number of needs changes for different MH needs, and for successful and unsuccessful clients. Figures E.2 (a to d) show changing needs for the "security" MH level, for homeless women who exited the program at 3, 6, 9, and 12 month periods after entering the program.

Calculating the predicted probability of exiting successfully is based on a client's simulated ECOC level at different three-month periods in the study. Details of the algorithm are provided in Section E.3.5.

The classification algorithm chosen is an SVM algorithm [9] with the "radial basis function" kernel.

[9]SKLearn SVM Algorithm: *http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html*

Other classifiers were used but this classifier consistently had best results.



(a) (b) (c) (d)

Figure E.2: Average number of security needs for homeless women who exited the CHF-HF program at 0, 3, 6, 9 and 12 month periods

Variables Subjective Variables:

- Success state of a client, where Success $\in$ [Yes, No].
- Client demographics, as per Table E.6.
- Needs mapped to Maslow's hierarchy.

Independent Variables:

- Needs in a Maslow hierarchy (MH) at each three-month interval.
- Initial ECOC stage rules, as per Algorithm 2.
- State transition table for ECOC states, as per Table E.8.
- ML Levels considered for predicting probability of success.
- Minimum error rate for Algorithm 1 to assign weights to each ECOC stage ML level considered.

Dependent Variables:

- Success state of a client, where Success $\in$ [Yes, No].

Output Variables:

- Predicted probability of success.

- Precision score of a supervised learning classifier based on predicted probability of success.

To execute the experiment, three steps need to be completed:

Step 1: Determine a client's initial ECOC stage by evaluating their change from period at 0 months to 3 months, as per Algorithm 1.

Step 2: For each period where $month > 3$, the state transition table in Table E.8 produces the next ECOC stage of an agent based on its current stage and number of needs in each ML level.

Step 3: Improve results by adjusting weights for each MH need. In the case of combination of ECOC stages and demographics, separate weights were calculated for each group under different combinations of demographic used to build a predictive model. See Algorithm 2 for more details on calculating weights.

Problem Definition (Summary)

Table E.7: Definitions

k	:	ECOC need level attribute index, where $kinK$.
ne_k	:	ECOC need level considered to make predictions, where $k \in K, ne_k \in NE$
$P(ECOC_k)$	:	Probability of success for ne_k based on ECOC graph.
$row(\overline{P(ECOC)})$	:	Mean probability of success for record row based on the ECOC graph.
$row(Succ)$	:	Success state of client in record row where $row(Succ) \in [0,1]$ for "failed" and "successful."
e_k	:	Error e for ECOC level of ne_k.
$\overline{e_k}$	:	Mean error for need ne_k for entire dataset.
$\overline{e}$	:	Mean error for entire dataset.
w	:	Weights assigned to all needs in NE for the entire dataset.
w_k	:	Weight assigned to need ne_k.

Objective Function (Summary)

$$min(\overline{e}) \tag{E.1.a}$$

such that: (E.1.b)

$$e_k = \frac{(P(ECOC_k) \times w_k) - row(Succ)}{(P(ECOC_k) \times w_k) + row(Succ)}$$

$$w = w \times (1 - \overline{e}) \tag{E.1.c}$$

E.3.3 Results

The best results occurred with the probability of success for each ECOC stage in Figure E.3.

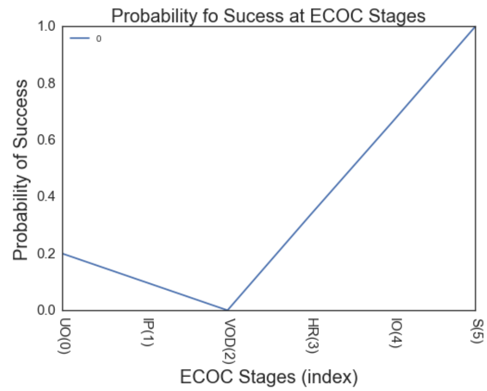


Figure E.3: Probability of success at different ECOC stages

By simulating a client's transition through ECOC stages, the model presented here increases the predictive capability of the model by 8% over relying on top demographics only, and by an additional 3% over Maslow's hierarchy only in Experiment 2.

E.3.4 Analysis and Discussion

The increase in predictive power of ECOC stages is not as high as was expected. However, future work in evaluating the level of overfitting looks to show a better quality model being generated by ML level of needs. Also, a more robust weight assignment algorithm should be used to identify global minimums.

It should be noted that by relying only on transitions in ECOC stages, higher predictions was made compared to relying on demographics alone. Also relying on transitions through ECOC stages plus only the 'MentalProb-k' demographic produced the highest precision score at 76%. This is an increase of 9% over only the 'MentalProb-k' demographic, and a 4% increase over 'MentalProb-k' plus number of needs at different MH levels.

E.3.5 Experiment 3 Supplementary Material

This section provides supplementary material about the models used in Experiment 3. Specifically, it provides details about the ECOC state machine and weight calculation algorithm. The objective of the algorithm is to reduce the difference between the probability of success according to ECOC graph (P(ECOC)) in Figure E.3 and the client's actual Success status in the attribute "Success."

ECOC State Machine Definition

The state machine in Algorithm 1 initializes an agent's first ECOC stage based on the differences between number of goals during the first and second time steps. The state transitions in Table E.8 transition an agent between ECOC stages based on goal changes in subsequent time steps. Generally, a reduction in the number of goals between time steps transitions the agent to the next optimistic ECOC stage. An increase in number of goals transitions the agent into the next pessimistic ECOC stage.

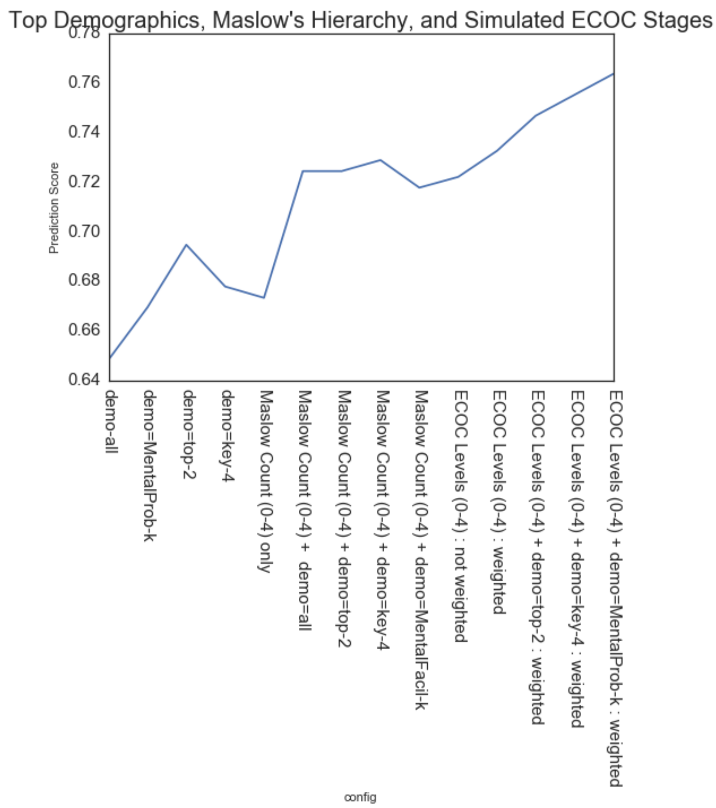


Figure E.4: Prediction based simulated changes in ECOC stages, compared to top Demographics and Maslow's hierarchy

Table E.8: ECOC State Transition Table

	ECOC Stages	**UO(0)**	**IP(1)**	**VOD(2)**	**HR(3)**	**IO(4)**	**S(5)**
Description	$\boldsymbol{diff}$						
More needs in previous period	1	1	2	2	2	3	5
Less needs in previous period	-1	4	3	3	4	5	5
No change from previous period	0	0	1	2	3	4	5

Prediction Model: Reinforcement Learning

This model uses reinforcement learning to calculate weights assigned to each ECOC level. The weights adjusts the shape of the initial ECOC graph in Figure E.3. Weight assignment is done on a particular group of agents. In this experiment, the weights are assigned to different groups of demographics.

Problem Definition

Table E.9: Definitions (Full)

NE	:	ECOC need level attributes considered to make predictions, where $K = \|NE\|$
k	:	ECOC need level attribute index, where $kinK$.
ne_k	:	ECOC need level considered to make predictions, where $k \in K, ne_k \in NE$
$P(ECOC_k)$	:	Probability of success for ne_k based on ECOC graph.
$row(\overline{P(ECOC)})$	:	Mean probability of success for record row based on the ECOC graph.
$row(Succ)$	:	Success state of client in record row where $row(Succ) \in [0,1]$ for "failed" and "successful."
e_k	:	Error e for ECOC level ne_k.
$\overline{e_k}$	:	Mean error for need ne_k for entire dataset.
$\overline{e}$	:	Mean error for entire dataset.
w	:	Weights assigned to all needs in NE for the entire dataset.
w_k	:	Weight assigned to need ne_k.
err_{min}	:	Minimum error required before finishing search for weight w assignment.
$bucket_{min}$	:	Minimum size of group size to calculate w. If size is too low default weights are returned.
$iter_{max}$	:	Maximum iterations of searching weight w assignments.

Algorithm 1 ECOC Transition Algorithm

```
procedure initECOCStage(needs_i, needs_{i-1})
    # This procedure sets a client's initial ECOC stage based on needs from
    # previous (needs_{i-1}) and current (needs_i) needs for each level of Maslow's
    # hierarchy ml ∈ ML.
    for all ml ∈ ML do
        diff = needs(ml)_{i-1} − needs(ml)_i
        curr = needs(ml)_i
        if diff ≥ 5 then
            ECOC(ml)_{i-1}) = 0
        else if diff ≥ 1 ∧ curr > 5 then
            ECOC(ml)_{i-1}) = 1
        else if diff ≥ 1 ∧ curr > 1 then
            ECOC(ml)_{i-1}) = 2
        else if diff ≥ 1 ∧ curr == 0 then
            ECOC(ml)_{i-1}) = 2
        else if diff == 0 ∧ curr > 5 then
            ECOC(ml)_{i-1}) = 2
        else if diff == 0 ∧ curr > 1 then
            ECOC(ml)_{i-1}) = 3
        else if diff == 0 ∧ curr == 0 then
            ECOC(ml)_{i-1}) = 3
        else if diff ≤ −5 ∧ curr > 5 then
            ECOC(ml)_{i-1}) = 3
        else if diff ≤ −5 ∧ curr > 1 then
            ECOC(ml)_{i-1}) = 4
        else if diff ≤ −5 ∧ curr == 0 then
            ECOC(ml)_{i-1}) = 0
        else if diff ≤ −1 ∧ curr > 5 then
            ECOC(ml)_{i-1}) = 3
        else if diff ≤ −1 ∧ curr > 1 then
            ECOC(ml)_{i-1}) = 3
        else if diff ≤ −1 ∧ curr == 0 then
            ECOC(ml)_{i-1}) = 3
        end if
    end for
    return ECOC
end procedure
```

Algorithm 2 ECOC Model Learning Algorithm

1: **procedure** ecocProb(ne, w)
2:     ***# This procedure assigns a weighted probability to the ECOC level passed in ne.***
3:     $ECOC = [0.2, 0.1, 0.0, 0.33, 0.66, 1.0]$
4:     $i = ECOC[ne]$
5:     **return** $i \times w$
6: **end procedure**

1: **procedure** assignECOC($subset, NE$)
2:     ***# Assign ECOC probabilities to subset by calling*** ecocProb() ***for each ECOC***
3:     ***# level in NE.***
4:     ***# This procedure is similar*** assignWeightedECOC() ***but without learned***
5:     ***# weights, hence all weights are set to 1 on line 6.***
6:     **for all** $row \in subset$ **do**
7:         **for all** $ne_k \in row$ **do**
8:             $row(P(ECOC_k))$ = ecocProb($ne_k, 1.0$)
9:         **end for**
10:         $row(P(ECOC)) = P(\overline{ECOC_k})$ for $k \in |NE|$
11:     **end for**
12:     **return** $subset$ with non-weighted $P(ECOC)$ assigned.
13: **end procedure**

1: **procedure** trainECOCModel($training, NE, w, err_{min}, bucket_{min}, iter_{max}$)
2:     ***# Find weights for training set based on ECOC levels in NE.***
3:     $iterations = 0$
4:     **if** $|training| \geq bucket_m in$ **then**
5:         $\overline{e} = 1.0$
6:         **while** $\overline{e} > err_{min}$ and $iterations < iter_{max}$ **do**
7:             **for all** $w_k \in w$ **do**
8:                 **for all** $row \in training$ **do**
9:                     $P(ECOC_k)$ = ecocProb(ne_k, w_k)
10:                     $e_k = \dfrac{P(ECOC_k) - row(Succ)}{P(ECOC_k) + row(Succ)}$
11:                 **end for**
12:                 $w = w \times (1 - \overline{e})$
13:             **end for**
14:         **end while**
15:     **end if**
16:     **return** w
17: **end procedure**

1: **procedure** assignWeightedECOC($subset, NE, w$)
2:     ***# Apply weights w to data subset***
3:     **for all** $w_k \in w$ **do**
4:         **for all** $row \in subset$ **do**
5:             **for all** $ne_k \in row$ **do**
6:                 $P(ECOC_k)$ = ecocProb((ne_k, w_k)
7:             **end for**
8:         **end for**
9:         $w = w \times (1 - \overline{e})$
10:         $row(P(ECOC)) = \overline{P(ECOC_k)}$ for $k \in |NE|$
11:     **end for**
12:     **return** $subset$ with weighted $P(ECOC)$ assigned.
13: **end procedure**

E.4 Experiment 4: Predict exit status using LSTM recurrent neural network

E.4.1 Introduction

The purpose of the experiment presented here is to find a model capable of predicting when a client will exit an intervention program, focusing on clients who exited the program in the first 12 months. The model is based on the client's MH needs and demographics. The experiment determines when certain demographics leave the program with a high enough precision. By showing precision score up to certain time points, we can narrow the scope of predicting client exit status for specific exit periods. It relies on a recurrent neural network (RNN) with long short-term memory unit (LSTM) to classify exit periods based on actual trajectory of client goals categorized by levels of Maslow's hierarchy and their demographics. The results are compared to those produced by traditional classifiers using demographic information only.

Hypothesis: A seemingly "irrational" client's exit from a program can be predicted better when considering their changing needs in a program rather than just demographics at intake.

The results of this experiment provide proof that tracking changes in client needs can help in predicting client exit periods in the target intervention program, and that client needs mapped to MH levels are a good metric for tracking progress. The resulting model makes good predictions (≥ 0.7) for certain demographics that can be made at the zero-month and after six-month periods in the program.

E.4.2 Experiment Design

This experiment uses the factorial-experiment design described by Barton [16]. The experiment uses different classifiers and combination of attributes to find the model with highest precision.

Method

The models presented here are the results of a Recurrent Neural Network (RNN) [10] with long short-term memory unit (LSTM) [11] [1, 212]. See Table E.10 for the RNN configuration parameters. For comparison, Table E.14 shows standard classifiers using all demographics at intake. Table E.15 shows the precision of classifiers split by demographic. The following classifiers were used. Note that SVM was producing precision but low recall rate. These results were omitted.

LogReg: Logistical regression [12].

SVM: Support vector machines [13].

KNN: k-nearest neighbour [14].

NaiveBayes: Naive Bayes classifier with gaussian distribution [15].

[10] TensorFlow RNN Package: *https://www.tensorflow.org/api_guides/python/contrib.rnn*
[11] LSTM: *https://www.tensorflow.org/api_docs/python/tf/contrib/rnn/LSTMCell*
[12] Logistical regression: *http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html*.
[13] Support vector machines: *http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html*.
[14] k-nearest neighbour: *http://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html*.
[15] Naive Bayes: *http://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.GaussianNB.html*.

Tree Regr: 1-dimensional decision tree regression [16].

RandomTreeRegr: Random forest regressor [17].

NN: Multi-layer Perceptron classifier [18].

NNReg: Multi-layer Perceptron regressor [19].

The classification algorithm chosen is the Recurrent Neural Network (RNN) [20] with long short-term memory unit (LSTM) [21] [1, 212].

Unlike traditional feedforward neural networks, RNN+LSTM have cyclic connections making them suitable for modelling sequences like those found in time-series data. ΔG is a time-series dataset and can benefit from this type of classifier. For comparison, in previous experiments that attempted to predict a client's exit status directly, relied on a feed forward neural network and support vector machines. The highest prediction score reached by these models was 0.76 using ΔG_{act} and a single demographic, history of mental health issues, as per Appendix E.3. The results presented here that rely on RNN+LSTM to reach 0.70 and above for a number of demographics. Being able to rely on more demographics allows the predictive model to be used for a more diverse population.

A variety of RNN configurations were evaluated. The RNN configuration that produced the best results were used in the final results presented. These are listed in Table E.10.

Table E.10: RNN Classifier Configuration

Variable	**Value**	**Description**
Training Set	0.7	Portion of the dataset used to train the model.
Testing Set	0.3	Portion of the dataset used to test the model.
Batch Size	30	Size of batch to train the model.
Max Iterations	3,000	Maximum number of iterations to train the model before stopping.
Dropout	0.7	Portion of the input that are masked during training [91].
Number of Layers	3	Number of layers of stacked RNN's.
Hidden Size	120	Number of memory cells in a layer.
Max Grad Norm	5	Maximum gradient norm during training for clipping values of multiple tensors by the ratio of the sum of their norms.
Learning Rate	0.005	Adam optimizer learning rate [132].

Variables

The following variables are used by the RNN classifier to build predictive models. The time-series data represents the number of needs at 3-, 6, 9-, and 12-month time periods. ΔG_{act} is presented as a time-series dataset of needs from one period to another.

[16] Decision Tree regression: *http://scikit-learn.org/stable/auto_examples/tree/plot_tree_regression.html*.

[17] Random forest regressor: *http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html*.

[18] Multi-layer Perceptron classifier: *http://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPRegressor.html/*

[19] Multi-layer Perceptron regressor: *http://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html/*

[20] TensorFlow RNN Package: *https://www.tensorflow.org/api_guides/python/contrib.rnn*

[21] LSTM: *https://www.tensorflow.org/api_docs/python/tf/contrib/rnn/LSTMCell*

Table E.11: Dependent Variables

Variable	**Description**
Demo	Client demographics, as per Table E.6 in Appendix E.2.
t	Current cycle being predicted, where $t = ExitPeriod$ for exiting records.
ΔG_{act}	Goal trajectory at each level of Maslow's hierarchy (MH), for each three-month interval.
$\Delta G_{act,t}$	Same as ΔG_{act} but limited to periods from 0 to t.

Table E.12: Independent Variables

Variable	**Description**
ExitStatus	Predicted outcome of a client, where $ExitStatus \in \{0, 1, 2\}$ for failed, successful, and missing.

The classification models are evaluated using precision of the model in Table E.13.

Table E.13: Output Variable

Variable	**Description**
Precision	Score of model, as per Equation E.2.

$$\text{Precision} = \frac{\text{True Positives} + \text{True Negatives}}{\text{All Positives} + \text{All Negatives}} \tag{E.2}$$

E.4.3 Results

Using key demographics, classifier models produced the following results. Models using all demographics as features are presented in Table E.14. Models using each demographic individually as features are presented in Table E.15.

Table E.14: Precision for classifiers predicting exit period using all key demographics

Classifier	**Precision**
KNN	0.221
NaiveBayes	0.303
NN	0.233
NNReg	-0.438
LogReg	0.331

Table E.15: Precision for classifiers predicting exit period using key demographics individually

Demo	**LogReg**	**KNN**	**NaiveBayes**	**NN**	**NNReg**
AbsRel-k	0.327	0.339	0.327	0.327	-0.021

Table E.15: Precision for classifiers predicting exit period using key demographics individually

Demo	**LogReg**	**KNN**	**NaiveBayes**	**NN**	**NNReg**
Addict-k	0.267	0.304	0.267	0.267	-0.016
CIC-k	0.248	0.269	0.248	0.269	-0.022
EmpAbility-k	0.307	0.378	0.307	0.307	-0.001
Employed-k	0.315	0.24	0.314	0.315	-0.008
FamilySitu-k	0.267	0.423	0.275	0.285	-0.023
GAge-k	0.252	0.276	0.267	0.329	-0.021
Gender-k	0.376	0.417	0.376	0.376	-0.015
HealthFacil-k	0.267	0.31	0.313	0.264	-0.053
InstitutionalizedDays-k	0.258	0.382	0.225	0.258	-0.042
MentalFacil-k	0.328	0.328	0.328	0.328	-0.015
MentalIssue-k	0.267	0.341	0.267	0.267	-0.02
PhysProb-k	0.267	0.417	0.267	0.324	0.01
PrimRes-k	0.281	0.297	0.267	0.267	-0.031
Sector-k	0.303	0.347	0.303	0.303	-0.017
UempDur-k	0.269	0.225	0.312	0.295	-0.025

Next, Figure E.5 shows precision for all demographics where precision is above 0.7. For additional information, the results are separated by demographic, demographic value, and exit period. Table E.17 shows the entire model, including each individual demographic value ($Demo = d$).

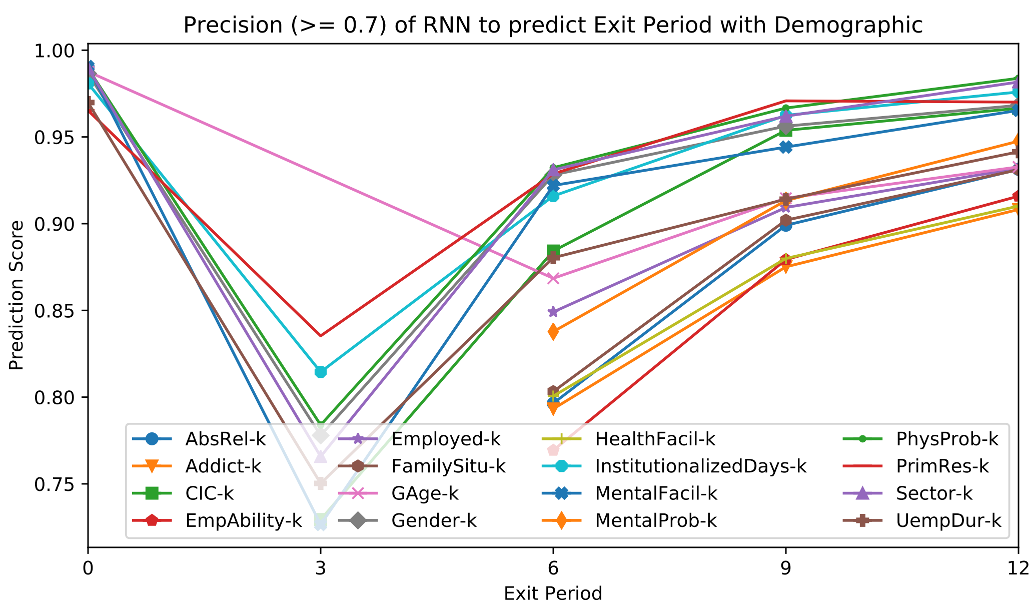


Figure E.5: Precision for demographics and count of needs at each three-month interval

Table E.16: Best RNN models for predicting $ExitPeriod$ with key $chf1$ demographics

Demo	**d**	**Exit Period**	**Precision Score**	$N(test)$	$N(train)$
PhysProb-k	Yes	0	0.998	163	378
PhysProb-k	No	0	0.981	152	353
Addict-k	Yes	3	0.53	333	776
Addict-k	No	3	0.618	227	527
FamilySitu-k	Single	3	0.502	394	919
FamilySitu-k	Single w Family	3	0.715	93	217
PhysProb-k	Yes	3	0.753	140	325
PhysProb-k	No	3	0.815	137	319
Addict-k	Yes	6	0.751	334	777
Addict-k	No	6	0.835	227	528
FamilySitu-k	Single	6	0.737	395	920
FamilySitu-k	Single w Family	6	0.869	93	217
PhysProb-k	Yes	6	0.916	141	326
PhysProb-k	No	6	0.949	138	319
Addict-k	Yes	9	0.861	334	777
Addict-k	No	9	0.889	227	528
FamilySitu-k	Single	9	0.858	395	920
FamilySitu-k	Single w Family	9	0.946	93	217
PhysProb-k	Yes	9	0.957	141	326
PhysProb-k	No	9	0.977	138	319
Addict-k	Yes	12	0.89	334	777
Addict-k	No	12	0.926	227	529
FamilySitu-k	Single	12	0.909	395	920
FamilySitu-k	Single w Family	12	0.953	93	217
PhysProb-k	Yes	12	0.98	141	326
PhysProb-k	No	12	0.988	138	320

E.4.4 Analysis and Discussion

The classifiers in Tables E.14 and E.15 did not produce results better than RNN models. Best precision score was 0.403 using the *FamilySitu-k* demographic with the KNN classifier.

The RNN model presented here does a good job for some of the key demographics selected. The model can predict, with precision of 0.998 clients that exited at exit period 0, given their demographic is $PhysProb\text{-}k = Yes$. Meaning, for anyone who is experiencing physical problems with a particular $\Delta G_{act,0}$ trajectory and exists at the beginning of the program, the model can predict this with 0.998 accuracy. Note that the goal trajectory at exit period 0 represents a client who is discharged right away. This may be due to a transfer to another program or having the client decide to leave the target program. Referencing Table E.16, the training set included 378 (Yes) and 353 (No) records, tested with 163 (Yes) and 152 (No) records. In total, 856 participants with a confirmed and untreated physical problem status or with a confirmed healthy status left the program at the zero-month period.

Our hypothesis stated that a sufficiently good prediction has a minimum 0.7 precision value. At the three-month period, $FamilySitu\text{-}k = Single$ and both values of *Addict-k* are below this minimum, hence cannot be used. The demographic value $FamilySitu\text{-}k = Single\,w\,Family$ and both values of

PhysProb-k can be used to predict whether a client will exit at the three-month period. After the three-month period, all key demographics can be used to make predictions, since each RNN model had a prediction score above 0.7.

Based on this analysis, we say that our hypothesis is proven true. By considering certain demographics and changes in MH needs, it is possible to predict exit periods in the CHF-HF intervention program better than other classifiers that do not consider changing needs of clients as a time-series. The changes in MH goals (ΔG_{act}) in combination with key demographics is a valid predictive measure over just using demographics at baseline. Good predictions can be made after the six-month time period. Noting the high representation of clients for testing ($N(test)$) and training ($N(train)$) in Table E.16, we can say that RNN predictive model is a good presentation of the sample population used to derive the model. Based on the low precision score at the three-month period, we can conclude that this time is the most dynamic period, and most difficult to predict.

E.4.5 Experiment 4 Supplementary Material

Complete results for RNN model on individual demographics.

Table E.17: All RNN models for predicting exit period using key demographics individually

Demo	**d**	**Exit Period**	**Precision Score**	$N(test)$	$N(train)$
InstitutionalizedDays-k	-0.0	0	0.991	266	620
InstitutionalizedDays-k	0.0-66.0	0	0.971	68	158
PrimRes-k	Emergency shelter	0	0.983	151	352
PrimRes-k	Couch	0	0.996	68	156
PrimRes-k	Addiction Facility	0	0.944	37	84
PrimRes-k	Rent/Long-Term	0	0.938	30	67
GAge-k	36-50	0	0.988	110	255
GAge-k	51+	0	0.99	82	191
GAge-k	25-35	0	0.993	93	215
GAge-k	0-24	0	0.979	61	142
MentalFacil-k	No	0	0.991	322	750
UempDur-k	Unknown	0	0.997	111	256
UempDur-k	More than 3 years	0	0.93	67	156
UempDur-k	12+ months	0	0.991	68	158
UempDur-k	6 to 12 months	0	0.942	49	112
UempDur-k	0 to 5 months	0	0.988	52	120
PhysProb-k	Yes	0	0.998	163	378
PhysProb-k	No	0	0.981	152	353
Sector-k	Single	0	0.992	200	465
Sector-k	Family	0	0.987	89	206
Gender-k	Male	0	0.988	152	353
Gender-k	Female	0	0.985	162	375
EmpAbility-k	No	3	0.474	338	786
EmpAbility-k	Yes	3	0.562	287	668
Addict-k	Yes	3	0.53	333	776
Addict-k	No	3	0.618	227	527
HealthFacil-k	No	3	0.531	397	925

Table E.17: All RNN models for predicting exit period using key demographics individually

Demo	**d**	**Exit Period**	**Precision Score**	$N(test)$	$N(train)$
HealthFacil-k	Yes	3	0.663	157	365
FamilySitu-k	Single	3	0.502	394	919
FamilySitu-k	Single w Family	3	0.715	93	217
AbsRel-k	Absolute	3	0.512	348	812
AbsRel-k	Relative	3	0.63	183	424
Employed-k	No	3	0.61	266	620
Employed-k	No - Unable to work	3	0.621	152	352
Employed-k	F/T	3	0.7	60	140
Employed-k	P/T	3	0.745	54	123
GAge-k	36-50	3	0.583	172	400
GAge-k	51+	3	0.605	130	303
GAge-k	25-35	3	0.695	135	312
GAge-k	0-24	3	0.802	85	197
MentalIssue-k	Yes	3	0.589	244	569
MentalIssue-k	No	3	0.638	219	511
UempDur-k	Unknown	3	0.719	130	303
UempDur-k	More than 3 years	3	0.723	106	247
UempDur-k	12+ months	3	0.765	98	226
UempDur-k	6 to 12 months	3	0.763	67	156
UempDur-k	0 to 5 months	3	0.782	63	147
InstitutionalizedDays-k	-0.0	3	0.669	215	500
InstitutionalizedDays-k	0.0-66.0	3	0.96	64	147
CIC-k	Canadian Citizen	3	0.729	273	635
Gender-k	Male	3	0.739	142	329
Gender-k	Female	3	0.817	151	352
PhysProb-k	Yes	3	0.753	140	325
PhysProb-k	No	3	0.815	137	319
MentalFacil-k	No	3	0.727	257	598
Sector-k	Single	3	0.784	179	415
Sector-k	Family	3	0.748	74	171
PrimRes-k	Emergency shelter	3	0.801	116	269
PrimRes-k	Couch	3	0.864	55	126
PrimRes-k	Addiction Facility	3	0.841	33	75
EmpAbility-k	No	6	0.712	338	788
EmpAbility-k	Yes	6	0.827	287	669
Addict-k	Yes	6	0.751	334	777
Addict-k	No	6	0.835	227	528
HealthFacil-k	No	6	0.768	398	927
HealthFacil-k	Yes	6	0.834	157	365
FamilySitu-k	Single	6	0.737	395	920
FamilySitu-k	Single w Family	6	0.869	93	217
AbsRel-k	Absolute	6	0.742	349	813
AbsRel-k	Relative	6	0.851	183	425
Employed-k	No	6	0.857	267	622

Table E.17: All RNN models for predicting exit period using key demographics individually

Demo	**d**	**Exit Period**	**Precision Score**	$N(test)$	$N(train)$
Employed-k	No - Unable to work	6	0.793	152	352
Employed-k	F/T	6	0.898	60	140
Employed-k	P/T	6	0.848	54	123
GAge-k	36-50	6	0.852	172	401
GAge-k	51+	6	0.812	131	303
GAge-k	25-35	6	0.895	135	313
GAge-k	0-24	6	0.915	85	197
MentalIssue-k	Yes	6	0.818	245	569
MentalIssue-k	No	6	0.857	220	512
UempDur-k	Unknown	6	0.871	130	303
UempDur-k	More than 3 years	6	0.865	106	247
UempDur-k	12+ months	6	0.885	98	228
UempDur-k	6 to 12 months	6	0.875	68	156
UempDur-k	0 to 5 months	6	0.906	63	147
InstitutionalizedDays-k	-0.0	6	0.855	216	502
InstitutionalizedDays-k	0.0-66.0	6	0.977	64	147
CIC-k	Canadian Citizen	6	0.884	273	637
Gender-k	Male	6	0.912	142	330
Gender-k	Female	6	0.944	152	352
PhysProb-k	Yes	6	0.916	141	326
PhysProb-k	No	6	0.949	138	319
MentalFacil-k	No	6	0.922	258	599
Sector-k	Single	6	0.91	179	417
Sector-k	Family	6	0.952	74	172
PrimRes-k	Emergency shelter	6	0.939	116	270
PrimRes-k	Couch	6	0.942	55	126
PrimRes-k	Addiction Facility	6	0.905	33	75
EmpAbility-k	No	9	0.851	338	788
EmpAbility-k	Yes	9	0.908	287	669
Addict-k	Yes	9	0.861	334	777
Addict-k	No	9	0.889	227	528
HealthFacil-k	No	9	0.862	398	927
HealthFacil-k	Yes	9	0.898	157	365
FamilySitu-k	Single	9	0.858	395	920
FamilySitu-k	Single w Family	9	0.946	93	217
AbsRel-k	Absolute	9	0.871	349	813
AbsRel-k	Relative	9	0.927	183	425
Employed-k	No	9	0.894	267	622
Employed-k	No - Unable to work	9	0.873	152	352
Employed-k	F/T	9	0.933	60	140
Employed-k	P/T	9	0.936	54	123
GAge-k	36-50	9	0.91	172	401
GAge-k	51+	9	0.85	131	303
GAge-k	25-35	9	0.956	135	313

Table E.17: All RNN models for predicting exit period using key demographics individually

Demo	**d**	**Exit Period**	**Precision Score**	$N(test)$	$N(train)$
GAge-k	0-24	9	0.942	85	197
MentalIssue-k	Yes	9	0.889	245	569
MentalIssue-k	No	9	0.938	220	512
UempDur-k	Unknown	9	0.918	130	303
UempDur-k	More than 3 years	9	0.877	106	247
UempDur-k	12+ months	9	0.922	98	228
UempDur-k	6 to 12 months	9	0.921	68	156
UempDur-k	0 to 5 months	9	0.932	63	147
InstitutionalizedDays-k	-0.0	9	0.929	216	502
InstitutionalizedDays-k	0.0-66.0	9	0.996	64	147
CIC-k	Canadian Citizen	9	0.954	273	637
Gender-k	Male	9	0.936	142	330
Gender-k	Female	9	0.976	152	352
PhysProb-k	Yes	9	0.957	141	326
PhysProb-k	No	9	0.977	138	319
MentalFacil-k	No	9	0.944	258	599
Sector-k	Single	9	0.945	179	417
Sector-k	Family	9	0.979	74	172
PrimRes-k	Emergency shelter	9	0.958	116	270
PrimRes-k	Couch	9	0.979	55	126
PrimRes-k	Addiction Facility	9	0.975	33	75
EmpAbility-k	No	12	0.892	339	788
EmpAbility-k	Yes	12	0.94	287	669
Addict-k	Yes	12	0.89	334	777
Addict-k	No	12	0.926	227	529
HealthFacil-k	No	12	0.913	398	928
HealthFacil-k	Yes	12	0.907	157	365
FamilySitu-k	Single	12	0.909	395	920
FamilySitu-k	Single w Family	12	0.953	93	217
AbsRel-k	Absolute	12	0.926	349	813
AbsRel-k	Relative	12	0.937	183	426
Employed-k	No	12	0.935	267	623
Employed-k	No - Unable to work	12	0.892	152	352
Employed-k	F/T	12	0.953	60	140
Employed-k	P/T	12	0.948	54	123
GAge-k	36-50	12	0.919	172	401
GAge-k	51+	12	0.902	131	303
GAge-k	25-35	12	0.948	135	314
GAge-k	0-24	12	0.962	85	197
MentalIssue-k	Yes	12	0.931	245	569
MentalIssue-k	No	12	0.964	220	513
UempDur-k	Unknown	12	0.945	130	303
UempDur-k	More than 3 years	12	0.933	107	247
UempDur-k	12+ months	12	0.944	98	228

Table E.17: All RNN models for predicting exit period using key demographics individually

Demo	**d**	**Exit Period**	**Precision Score**	$N(test)$	$N(train)$
UempDur-k	6 to 12 months	12	0.932	68	156
UempDur-k	0 to 5 months	12	0.954	63	147
InstitutionalizedDays-k	-0.0	12	0.96	216	503
InstitutionalizedDays-k	0.0-66.0	12	0.992	64	147
CIC-k	Canadian Citizen	12	0.967	273	637
Gender-k	Male	12	0.957	142	330
Gender-k	Female	12	0.979	152	353
PhysProb-k	Yes	12	0.98	141	326
PhysProb-k	No	12	0.988	138	320
MentalFacil-k	No	12	0.965	258	600
Sector-k	Single	12	0.975	179	417
Sector-k	Family	12	0.988	75	172
PrimRes-k	Emergency shelter	12	0.981	116	270
PrimRes-k	Couch	12	0.959	55	126
PrimRes-k	Addiction Facility	12	0.97	33	75

E.5 Experiment 5: System Evaluation Report

E.5: Experiment 5: System Evaluation Report

Appendix E.5: System Evaluation

Appendix E.5: Figures

Appendix E.5: Tables

Appendix E.5: System Evaluation

1. Introduction

This appendix contains the full experiment report for Series 1 and Series 2 experiments introduced in Chapter 7. The main hypothesis introduced in Chapter 1 of this thesis stated that seemingly "irrational" behaviour can be emulated using a rational reasoner. The experiments presented here attempt to confirm or deny this hypothesis by testing six sub-hypotheses that collectively ask which components of a cognitive model presented by the thesis are sufficient to create a cognitive model of a human-like agent. Human like agents are represented as housing first participants in a study conducted by the Calgary Homeless Foundation (CHF-HF). The experiments are designed as fractional-factorial experiments modelled after Barton [16]. Each cognitive component represents a factor used to create tests with different combinations of factors. The results of the experiments indicate that human-like cognitive components do produce trajectories that resemble actual trajectories found in CHF-HF data. There are two key conclusions of the experiments. First, some form of replanning is required to emulate the changing needs of clients. Second, emotional components emulate replanning and goal reranking more accurately than simply relying on bounded rationality exhibited by an agent.

To determine whether a model sufficiently emulates an actual human agent is based on two metrics. The first metric is accuracy that indicates the model's ability to successfully identify a match between actual and simulated trajectories. The second metric is an error threshold that defines what is considered a sufficient "match." The indicator used to calculate the error is the number of goals per Maslow's level an actual and simulated agent has at a given point in time. The error selected is the mean absolute error (MAE) between real requests made and simulated requests of an agent. Given the mean MAE for an entire model across all trajectories, accuracy measures how well the model performed in identifying a match, given an MAE threshold.

As the baseline model, we begin with a classically rational model with boundless cognitive resources and a neoclassical evaluation function that maximizes utility. Through a series of experiments, the model is incrementally modified by adding human-like cognitive components introduced in this thesis. For each new model, the rational goal reasoner STRIPS-BR introduced in Section 5.4 is used to generate and select plans. The simulation in Section 5.7 is used to emulate how such an agent's behaviour may change while interacting with their environment. This simulated behaviour is compared to the real behaviour found in the CHF-HF data.

As was discussed in Chapter 4 one of the objectives of this work was to identify factors that were observable by a bounded observer. Hence, in addition to the rationality of a model, the evaluation of experiment results incorporates the degree to which each factor is observable. Factors that are easier to observe are preferred over those that are harder to observe. For example, BRAMA's representation of cognitive and time bounds are an approximation for the subject's actual cognitive limitations. As these are difficult characteristics to capture explicitly they are less observable than other factors. A decision strategy is a proxy to the level of commitment and foresight someone expresses about their long-term decisions. For example, someone may have limited foresight (myopic), perfect foresight (resolute), or be medium foresight (sophisticated). Observations like these can be inferred by evaluating a subject over an extended period of time. The ECOC threshold is a proxy for the subject's emotional state. Since emotions are often expressed externally, the threshold may be observed if sufficient trust exists between the subject and the observer. Finally, the preferred ranking of goals may be observable if the order of requests matched the agent's preferences. Provided the service constraints are known, the practical order is observable through scheduling constraints placed on the service providers. Finally, Maslow's order is assumed to have a relatively high observability due to the domain-specific mappings presented in Chapter 6.

1.1. Hypothesis

The purpose of experiments presented here is to answer our main hypothesis:

> **Main hypothesis:** Seemingly "irrational" behaviour can be emulated using a rational reasoner.

To test this hypothesis, six sub-hypotheses are tested. These are split between two series of experiments that test each extension of the BRAMA cognitive agent model. Each extension adds a human-like factor discussed throughout the thesis, and deemed rational when incorporated by a bounded human-like agent. For example, bounded rationality is a natural limitation, and actions that maximize utility within those limits are deemed rational. Hypothesis 2 explicitly addresses rationality by evaluating the lack of utility maximization to test whether agents with cognitive and other limitations are perceived to act irrationally. Different decision strategies are used that match the agent's predetermined disposition to risk and perceived knowledge about the future. Also, an agent's emotions are not under their control but play an important role in perceiving our environment and assigning utility. Hence individual decisions made in a particular emotional state are rational within the agent's abilities to accommodate for their emotions.

Series 1 experiments address hypotheses 1 to 5:

> **Hypothesis-1:** Seemingly "irrational" behaviour can be emulated using a rational reasoner better with bounded rationality limits than without.

> **Hypothesis-2:** Seemingly "irrational" behaviour can be emulated using a rational reasoner better with plan utility maximization than without.

> **Hypothesis-3:** Seemingly "irrational" behaviour can be emulated using a rational reasoner better with myopic and sophisticated search strategies than without.

> **Hypothesis-4:** Seemingly "irrational" behaviour can be emulated using a rational reasoner better with Maslow's hierarchy as preferred goal ranking than without.

> **Hypothesis-5:** Seemingly "irrational" behaviour can be emulated using a rational reasoner better when maximizing ECOC expected utility than when maximizing the neoclassical expected utility function.

Series 2 experiments address hypothesis 6:

> **Hypothesis-6:** Seemingly "irrational" behaviour can be emulated using a rational reasoner better when replanning based on ECOC threshold than replanning based only on bounded rationality limits.

1.2. Analysis Summary

To answer the main hypothesis, the six hypotheses extend the BRAMA agent model with human-like factors discussed throughout the thesis. Each test simulates each agent's plans to achieve their individual goals with different configurations of factors. The experiment design and metrics assume that, if behaviour under the rational factors matches those exhibited by actual human agents, those human agents were themselves rational. Since homeless clients are deemed irrational by a bounded observer, proving each hypothesis will conclude that homeless clients being emulated are rational, provided the human-like factors are incorporated in the model. Analysis, then, is based on metrics that compare the actual human agent's behaviour to the simulated human-like agent behaviour. Specifically, a simulated agent's behaviour trajectory matches an actual human agent's behaviour trajectory if the accuracy of a model is high and the error threshold that constitutes a satisfactory match between trajectories is low.

The results of the experiments indicate that some form of replanning is required to emulate the changing needs of clients. Several mean absolute errors (MAE) were used to evaluate proper error thresholds for satisfactory models. Overall, the results indicate that a combination of the resolute strategy, a high ecoc-th value (≥ 0.2), and either low or medium BR(C) value can be used to emulate how goals are reranked by CHF participants. Hence, a client's cognitive limitations and their emotional state are suitable factors for emulating their behaviour.

Based on the results presented here, more reliance may be placed on the emotional state of the agent which is easier to observe than other factors. Knowing an agent's cognitive bound may be more difficult without closer examination in a controlled setting, something not always possible with the homeless population. It may also be possible to tell which decision strategy a subject is using if they are observed to change their priorities frequently (myopic), act in a risk-neutral way (sophisticated) or stick to an initial plan for as long as possible (resolute with replanning).

2. Data

The Calgary Homeless Foundation (CHF)[1] has provided a dataset that captured information about clients as they participate in a "Housing First" (HF) intervention program administered by the CHF and its partner service providers. The CHF-HF dataset contains information on approximately 4,000 unique clients that participated in the HF program in Calgary from 2009 to 2015. Data continued to be collected through 2016. The information was collected using the HS Assessment questionnaires found at the CHF website[2]. For this analysis, 2,096 participants were included between 2012 and 2015.

2.1. Participant selection Process

CHF followed the following process for selecting participants.

1. Various "intake" forms are provided every time a client comes into a shelter participating with CHF in the Calgary region.
2. Among them, the Service Prioritization Decision Assistance Tool (SPDAT) questionnaire is administered on a continuous basis to clients in the Calgary region. SPDAT is a tool to assess a social service client's acuity. The answers provided by clients are self-reported with the help of service providers. These are not clinically verified.
3. A group of organization and intervention program administrators review each newly filled out SPDAT from the Calgary region to decide whether a client is suitable for their service offering of intervention program.
4. The HF program selects participants that have a high acuity level, indicating they are good candidates for the level of independence required by the program.

2.2. Data Gathering Procedures

CHF followed the following procedure to gather data.

1. Once a client is selected for the CHF HF program, they are contacted and a process for finding suitable housing begins.
2. Once housing is found, the client is relocated to the new location and given the move-in HF Assessment form: "Move-in-Assessment (v 7.27.2015)."
3. A follow-up HF Assessment questionnaire is administered every 3 months: "General-HS-HF-3-60-Month-Follow-Up-Interview (v 10.16.2015)."
4. When a client exists the program, successfully or otherwise, an exit HF Assessment form is administered: "Exit-Assessment (v 7.27.2015)."

2.3. Test Environment Configuration

The test environment configuration includes an action schema and agent configurations.

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[1] The Calgary Homeless Foundation: http://calgaryhomeless.com/.

[2] CHF Forms: http:// calgaryhomeless.com/ what-we-do/ oversee-hmis/ user-information-tools/ hmis-forms/ , Accessed November 21, 2016.

2.3.1. Action Schema Creation

Of the 58 requests types represented by OSSN an action schema was created for the 22 types. 43 CHF participants were selected that only requested one or more of the 22 request types, as listed in Table 1.

Table 1. Requests types from OSSN included in the tests.

Employment training	Income
Utility arrears	Clothing
Moving	Rent arrears
Tenant insurance support	Food
Health support	Debt reduction
Housing temp	Disability support
Clean Clothing	Medication
Hygiene	Security deposit
Addiction support	Identification
Child care	Housing supplement
Rent shortfall subsidy	Furniture

2.3.2. Agent Configuration

In the test environment, different combination of factors were created. In total, 133 different tests were conducted, one for each $\mathbb{M}$ configuration. Each configuration is a standalone test. For each test, an error score is computed to show how close the goal preferences of a simulated agent match those of their actual counterpart in the dataset. In addition to the 133 configurations, each of the 43 agents was initiated with goals as the requests the participant made for all three-month periods, and in the order given. All goals were included in the initial goal set. Any distribution of goals over multiple periods was done solely by the replanning and reranking algorithm.

2.3.3. Client Needs Trajectory

In addition to capturing client basic needs, HF Assessment also provides a trajectory of those needs over time. Follow up interviews at three-month intervals capture client needs as a time-series dataset. At each three-month interval, HF Assessment captures all the requests a client makes to the service provider. Figure 1 provides an example client with needs at each MH level from intake at time 0 up to the 12-month HF Assessment follow-up.

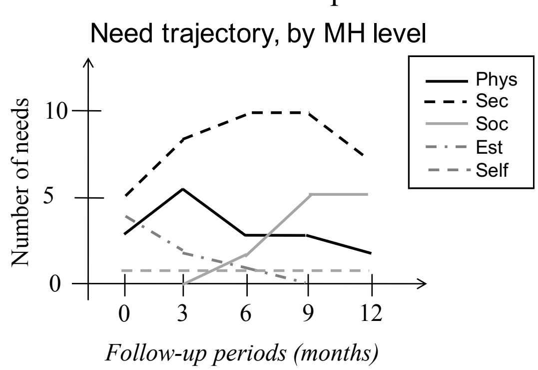


Figure 1. Example need trajectory of an agent from intake at time 0 to follow-up at 12.

3. Experiment

This section introduces the experiment, its goals, design, and evaluation criteria.

3.1. Experiment goals

The goals of the experiments presented here are to prove each sub-hypothesis. The metric for each experiment identifies factors that, with high accuracy, reduce the difference between time series data provided by CHF and simulation trace produced by BRAMA. In Figure 2 the goal hierarchy is presented. This experiment provides details about levels 5 to 7.

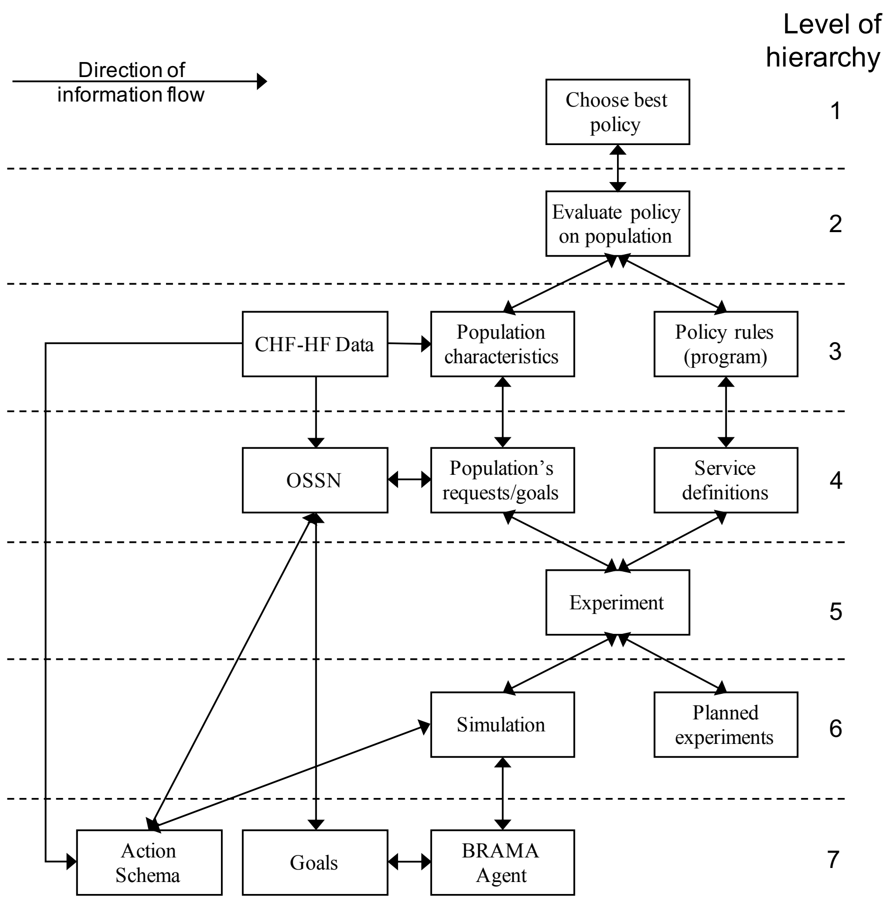


Figure 2. Experiment Goal Hierarchy for Social Service Policy Evaluation.

The overall goal of the project at level 1 is to choose the best social service policy for the target population. At level 2, an evaluation of policy on a given population is performed. At level 3, population characteristics and the policy's rules under a specific program are identified. Since this is implementation specific, a dataset is provided. In the context of this this experiment, the dataset provided by Calgary Homeless Foundation (CHF) about their Housing First (HF) program is referred to as CHF-HF. At level 4, a population's requests/goals and the services they use are defined. The requests/goals are categorized according to the Ontology of Social Service Needs (OSSN). At level 5 a series of experiments is defined. At level 6 the simulation environment and experimental design are defined. The points of interactions between the simulation and experiments are the variables and test configurations used for the experiments. Finally, at level 7 the BRAMA framework provides the models used to execute simulations for each experiment. It includes an action schema and goals categorized by OSSN. It also includes the BRAMA agent which is in part defined by the goals along with other variables, as discussed in Section 3.3.

3.2. Experiment Design

The experiment is a fractional-factorial experiment design. Factorial experiments are based on a grid, with each factor tested in combination with every level of every other factor. Factor levels are the values that each factor can take. For example, a two-level factor will have two values, say low and high, or -1 and 1. Unlike a factorial experiment, a fractional-factorial experiment has factors with different levels. For example, an experiment may have a mix of two-level and three-level factors. The experiment presented here is an eight-factor design that uses eight independent variables listed in Table 3. It contains three two-level factors, four three-level factors, and one four-level factor.

3.3. Variables

Dependent variables are those that are being tested, as listed in Table 2. The metrics described here are used to determine whether a model M produces simulated trajectories that match actual trajectories found in the data. The accuracy score determines how well a model matches agent configurations included in the test. Accuracy is calculated by

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where TP is the number of true positives, TF is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

Next, we must determine what is considered a sufficient condition for trajectories to be a match. For this, the distance between the number of goals in actual versus simulated periods is used to calculate the error. The error threshold, then, defines what is considered a match. The indicator used to calculate the error is the number of goals per Maslow's level an actual and simulated agent has at a given point in time. The error selected is the mean absolute error (MAE) between real requests made and simulated requests of an agent. Originally mean squared error was used as the error metric. The mean absolute error was chosen instead due to many outlier errors that skewed the results. Given the mean MAE for an entire model across all trajectories, accuracy then measures how well the model performed in identifying a match, given an MAE threshold.

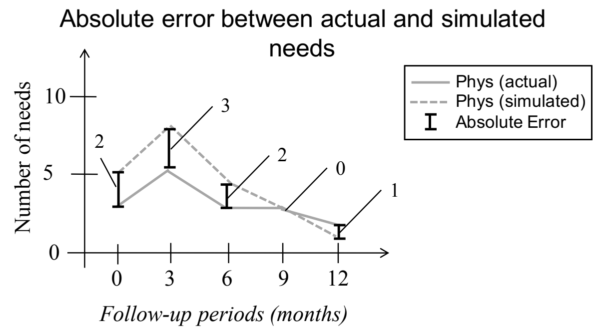


Figure 3. Example absolute error between actual and simulated physiological needs.

The difference between simulated and actual trajectories is calculated as the MAE between the goals of all periods in each trajectory. Consider again the trajectory of actual physiological needs in Figure 1. In Figure 3, the actual trajectory of physiological needs is shown again, along with the simulated trajectory of physiological needs. Each follow-up period represents the beginning and end of a cycle. A cycle represents the time an agent took to satisfy its goals. The absolute error (AE) is the difference between actual and simulated number of physiological goals at each time point between cycles.

Table 2. Dependent Variables.

Variable	**Values**	**Description**
Simulated goal trajectory	Goal count per period	Sum of goals at each MH level for each period in the simulated trajectory.
Accuracy	[0, 1]	Given an MAE threshold, the accuracy of a model M in matching simulated trajectory to the actual trajectories, as per Equation 1.
AE_{mh}	{0, 1, 2, ...}	Absolute error for Maslow's level *mh* between the number of goals in actual and simulated periods.
MAE_{mh}	{0, 1, 2, ...}	Mean absolute error (MAE) for Maslow's level mh of each agent in a model. MAE is used for comparing goal tra- jectories in the simulation trace to goal trajectory from CHF-HF data, defined in Equation 2. MAE represents the mean number of goals the actual and simulated tra- jectories differed by.
MAE_k	{0, 1, 2, ...}	Mean absolute error (MAE) of each agent *k* in a model. It is used for comparing goal trajectories in the simulation trace to goal trajectory from CHF-HF data, as per Equation 3. MAE_k represents the mean number of goals the actual and simulated trajectories differed by.
$MAE_{\mathbb{M}}$	[0, 1]	MAE for a model $\mathbb{M}$ configuration across all agents, as per Equation 4.

MAE-threshold	{0, 1, 2, ...}	MAE threshold for determining a cutoff for a good model.
True Positive (TP)	{0, 1, 2, ...}	Agent k with: $MAE_k \leq$ MAE-threshold and $(MAE_{\mathbb{M}} + 0.25) \leq$ MAE-threshold
True Negative (TN)	{0, 1, 2, ...}	Agent k with: $MAE_k >$ MAE-threshold and $(MAE_{\mathbb{M}} + 0.25) >$ MAE-threshold
False Positive (FP)	{0, 1, 2, ...}	Agent k with: $MAE_k \leq$ MAE-threshold and $(MAE_{\mathbb{M}} + 0.25) >$ MAE-threshold
False Negative (FN)	{0, 1, 2, ...}	Agent k with: $MAE_k >$ MAE-threshold and $(MAE_{\mathbb{M}} + 0.25) \leq$ MAE-threshold
True Positive Rate	[0, 1]	TPR = TP / (TP + FN), or 0 if (TP + FN) is equal to 0.
False Positive Rate	[0, 1]	FPR = FP/(FP+TN) , or 0 if (FP + TN) is equal to 0.

To calculate the error for the entire trajectory of needs for an MH level mh, the mean of all absolute errors at that level is taken as mean absolute error MAE_{mh} defined as

$$MAE_{mh} = \frac{\sum_{i=1}^{n} |G_i^{act} - G_i^{sim}|}{n}, \tag{2}$$

where mh is one of the five MH levels, $i \in \{1, ..., n\}$ is the period index, n is the number of time periods between cycles, G_i^{act} and G_i^{sim} are the sum of actual and simulated goals outstanding at period i, respectively.

$$MAE_k = \frac{\sum_{mh=1}^{5} MAE_{mh}}{5} \tag{3}$$

To calculate the MAE_k between actual and simulated trajectories for all levels, the mean of MAE_{mh} for all levels is calculated as the MAE_k in Equation 3.

$$MAE_{\mathbb{M}} = \frac{\sum_{k \in K} MAE_k}{|K|} \tag{4}$$

To calculate the $MAE_{\mathbb{M}}$ for a model $\mathbb{M}$, the mean of all MAE_k for each agent k in the model is calculated, as per Equation 4.

Finally, an aggregate MAE_k is one that uses aggregate periods to calculate the absolute error between actual and simulated periods. Recall that the MAE considers the difference between the number of actual and simulated goals at each period. However, as mentioned in Section 7.1.4, the actual length of a cycle and time between each period is domain or situation specific. Aggregate periods are those that combine multiple periods and are compared to aggregate and non-aggregate periods. For example, an actual client may take one day, week, or a month to consistently satisfy their goals. They then move onto other goals that may or may not be satisfied when the three-month period is over. The three-month period is simply a constraint enforced by the CHF-HF program. As a result, the data only shows a snapshot of what needs were unsatisfied for that cycle. Hence, while a simulated agent completes goals in one cycle, that cycle may represent one week, a month, a three month period, or two periods that last six months in total.

To compensate for the three-month constraint of the study, and the lack of information about how long each simulated cycle lasts in actual calendar time, and aggregate of absolute errors per period is calculated.

Consider the actual and simulated trajectories for physiological needs in Figure 4. In this example, the number of goals outstanding in the actual trajectory at each period are three goals at month 0, five at month 3, three at months 6 and 9, and two goals at month 12, with the trajectory being four cycles in total. The simulated trajectory, however, is made up of only three cycles to satisfy the same goals. The number of outstanding goals at each simulated period are five goals at period *w*, ten at the period *x*, three at period *y*, and one goal at period *z*.

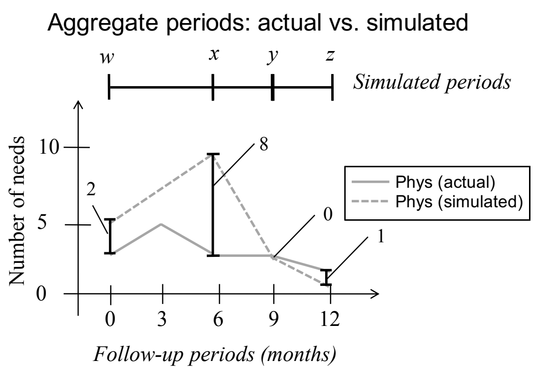


Figure 4. Example of aggregate periods.

Aggregate periods are those that combine multiple periods for calculating an absolute error. For example, the simulated cycle from periods *w* to *x* overlaps with actual periods 0, 3, and 6. The absolute error for physiological goals AE_{phys} between period 0 and *w* is not aggregated and is the same as in Figure 3, mainly $AE_{phys}=|5-3|=2$. To calculate the difference between simulated period *x* and its actual counterpart, actual periods 3 and 6 must be aggregated by summing their goals. The result is the actual aggregated goal number, mainly 5+3=8. To calculate AE_{phys}, this sum is subtracted from simulated period *x*, giving the aggregate $AE_{phys}=|10-8|=2$. For the remaining periods *y* with 9 and *z* with 12, AE_{phys} is calculated without aggregation. MAE_{phys} is then calculated as per Equation 2, where *n* is the smaller number between simulated and actual periods. Different combinations of actual and simulated aggregate and non-aggregate trajectories are used to align best pairs. The pair with lowest MAE_{mh} is chosen for calculating MAE for agent k error MAE_k , and the entire model MAE_M.

Independent variables are the factors that control each experiment configuration, as listed in Table 3. These are the factors being evaluated for their impact on the MAE.

Table 3. Independent Variables.

Variable	**Values** (actual quantity)	**Description**
Actual goal trajectory	goal count per period	Sum of goals at each MH level for each cycle in the actual trajectories in CHF-HF dataset.
BR(C)	h-bsln (no limit), m (70), l (40)	Cognitive bound defined as h-bsln for high used for baseline, m for medium and l for low.
BR(T)	h-bsln (50,000), m (10,000), l (5,000)	Time bound defined as h-bsln for high used for baseline, m for medium and l for low.
planutil	none, planutilswap	Plan selection criteria during the planning phase where none means select first plan found and planutilswap means find plan with highest utility.
strategy	myopic, soph, resolute, resolute-bsln	Planning strategy including myopic, sophisticated, resolute, and resolute-bsln for baseline which uses the resolute strategy.
pref	agent, MH, agent-bsln	Preference used by the agent during the execution phase, where agent means the agent's preferred order, MH means Maslow's order, and agent-bsln means baseline used agent order.
executil	exp, ecoc	Expected utility function used during the execution phase.
ecoc-th	0.0, 0.1, 0.2, 0.4, 0.6	ECOC threshold for triggering replanning. ecoc-th=0.0 means replanning is not triggered due to ECOC.
act-th	0.0, 0.1, 0.3, 0.6	Action utility used to select goals for deferment.

Nuisance variables are those that are known beforehand but cannot be controlled directly. These include environmental factors that are approximations of social services. The action schema *AS* is a nuisance variable.

Table 4. Nuisance Variables.

Variable	**Description**
AS_{BR}	Bounded action schema used by agent. For these tests, it is assumed that the agent knows only about correct actions.

Intermediate variables are those that are not controlled directly but through other independent variables. These include values internal to the agent model during simulation, including number of plans generated and run time.

Table 5. Intermediate Variables.

Variable	Description
Number of plans	Number of plans in the search tree generated by the BRAMA planner.
Run time	Time it took to simulate an agent. Only agents under 60 minutes are included in these experiments.

3.4. Evaluation Metrics

The hypothesis being tested is that seemingly "irrational" client captured by the CHF-HF dataset are acting rationally provided sufficient human-like factors are included in the model. The metrics are meant to identify those factors in the BRAMA model that reduce the error between simulated trace and actual CHF-HF data. The results will be evaluated on the accuracy of the model and mean absolute error (MAE). Different MAE thresholds will be used to test combinations of factors to find a suitable set of models. The Main Effects Plot graph will indicate which values for the factors had the best TPR versus FPR.

3.5. Methods and Materials

The BRAMA framework is implemented using SWI-Prolog version 6.2.6[3]. This includes the agent model, action schema, and simulation environment.

The analysis was performed using the Python[4] programming language. Database and statistical computing was performed using the Pandas[5] data analysis toolkit library. Visualizations were produced using Matplotlib[6] graphics environment.

Experiments were performed on a MacBook Pro[7], with a 2.4 GHz Intel Core i7 CPU and 8 GB of 1600 MHz DDR3 RAM.

3.6. Experiment Limitations

There are several limitations placed on the experiments that impact the testing of the hypotheses. These include limitations of the data provided by CHF and computational limitations of the simulation.

[3] SWI-Prolog version 6.2.6; Available at http://www.swi-prolog.org; Accessed on October 28, 2015
[4] Python Software Foundation. Python Language Reference, version 3.5.2. Available at http://www.python.org, Accessed on January
[5] Pandas Data Analysis Toolkit; Available at http://pandas.pydata.org/pandas-docs/version/0.20.2/index.html; accessed on June 4, 2017
[6] Matplotlib: A 2D Graphics Environment 2.2.2; Available at https://matplotlib.org/2.2.2/index.html; accessed on April 4, 2018
[7] Apply Inc. MacBook Pro; Available at https://www.apple.com/ca/macbook-pro/; accessed October 15, 2015

3.6.1. Data-Based Limitations

The main hypothesis states that seemingly irrational individuals are acting rationally but within human-centric limitations. The limitation of data in the homeless domain is the constraint that only observable factors should be used to configure an agent that emulates human-like behaviour. Several limitations are placed on the BRAMA agent which are meant to replicate the limitations placed on clients captured by CHF-HF data. However, not all factors are observable or captured by the data.

Client demographics and requests for basic needs are provided by the CHF data. The temporal order of each request is represented as a trajectory of requests. Its order is based on the order HF Assessment questionnaires were administrated, whether at intake, during follow-up visits, or during the exit interview. The simulations generate several trajectories using different configurations of the agent model, and match the simulated trajectories to those of the actual trajectories found in CHF data. Since only requests and demographics are provided, additional social science theories of behaviour are used to supplement the models with domain-specific modifications.

The OSSN ontology introduced in Chapter 6 relies on client demographics and basic needs to best align those requests with Maslow's hierarchy. The actual preferred ranking of goals a client has is not provided. Instead, the experiments assume that the requesting order is the preferred order. It is also not known if the services required to meet those needs are provided and utilized by the client. It is assumed that they have been, and that, unless the request is made again in a future questionnaire, the service was successfully utilized to satisfy their needs. The cognitive limitations of clients are also not provided. Hence, the exact bounds exhibited by clients is not known. Different configurations of bounds are evaluated to find ones that produce trajectories that match trajectories found in the data.

The emotional state of the clients is not provided. This makes it difficult to confirm whether a client is in fact in a pessimistic or an optimistic stage of ECOC, or whether they are following the neoclassical utility function. Instead, the assumption is made that if a simulated trajectory matches actual trajectory, the specified utility function matched the client's characteristic. When the neoclassical expected utility produces best match then emotions are assumed to not have played a role in the actual agent's decision making. If the ECOC utility is used to produce the best results, then emotions are assumed to have influenced the agent's decision making. Finally, the action schema identified in Appendix C and used in the simulation does not necessarily match that of the CHF service providers. Best efforts were made to ensure a reasonable representation is captured.

Decision strategies used by CHF participants are not provided. Instead, simulated trajectories with a low MAE_M are used to identify which client may be using a myopic or sophisticated strategy to change goals, and which are using the resolute strategy to keep goals static. In Series 2, it is assumed that goal reranking and replanning are based on emotions or bounded rationality, and only the resolute strategy is used.

Finally, the time frames for simulated trajectories are not known. While actual periods are three months apart, what happens in that time frame is not known. Hence, simulated periods may span more than one period, or multiple actual periods may span a single actual period.

3.6.2. Simulation Limitations

Due to computational limitations, several limits were placed on the simulation execution time. First, a time limit of 60 minutes was placed on each configuration. Fifteen configurations were excluded from the experiment analysis due to this constraint. Second, any simulation with an agent configuration that required more than 44 cycles for the simulation to finish were excluded from experiments, and are identified as “agerr” in the result tables in Appendix E.2. In total, fourteen agents were impacted and partially represented, across 81 simulation. The following tests were excluded from analysis as not enough samples were collected: 'tn066', 'tn067', 'tn068','tn045a', 'tn046a', 'tn047a', 'tn048a','tn006', 'tn007', 'tn015', 'tn016', 'tn024', 'tn025', 'tn033', 'tn034'.

Finally, due to limited execution time and available memory, limitations were placed on how large a search tree was possible. This made it difficult to generate and evaluate different utility functions and preferred orders that required a large search tree. For example, the “unbounded” time used for the baseline agent model was in fact bound with a high number to ensure the generated search tree was large enough to find many solutions, but also fit within the memory constraints of the test computer. Hence, not all possible plans were included in the tree and assigned a plan utility. Within the limits, variability in goal and action order was observed at the end of each plan, which produced small variations in overall plan utility. As a result, there was not a significant difference between plan utility and selected plans between models that used different factor configurations. Including the agent's preferred order ranking (*pref=agent*) to calculate utility versus Maslow's goal (*pref=MH*), which use neoclassical utility function (*executil=exp*) versus ECOC based function (*executil=ecoc*), or between models that maximize utility (*planutil=planswaputil*) versus models that choose the first plan found (*planutil=none*). In these cases, the initial order of goals played a more significant role than the plan utility in finding a plan that maximized plan utility.

4. Test Designs

There are 133 configurations of factors included in the tests. These are grouped into two series of tests; Series 1 has 41 tests and Series 2 has 92 tests.

4.1. Test Series 1

Series 1 tests include a baseline test and 40 configurations of the other factors.

4.1.1. Configuration: baseline

The baseline configuration represents classically "rational" agents. These agents are unbounded in their cognitive (*BR(C)=h*) and time (*BR(T)=h*) resources, use a search strategy that maximizes their utility (*planutil=planutilswap*), rely on the agent’s preferred goal order (*pref=agent*), employ a resolute decision strategy (*strategy=resolute*), and use classical expected utility function (executil=*exp)*.

testn	brc	brt	planutil	strategy	pref	executil
baseline	h	h	planutilswap	resolute	agent	exp

4.1.2. Configurations: 1-4

Same as baseline but agent does not maximize utility (planutil=none) with four permutations of different BR(C) and BR(T) values, where BR(C) and BR(T) l for l (low) or medium (m).

testn	brc	brt	planutil	strategy	pref	executil
tn001	l	l	none	resolute	agent	exp
tn002	l	m	none	resolute	agent	exp
tn003	m	l	none	resolute	agent	exp
tn004	m	m	none	resolute	agent	exp

4.1.3. Configurations: 5-13

This configuration tests different strategies, myopic, sophisticated, or resolute.

testn	brc	brt	planutil	strategy	pref	executil
tn005	m	m	none	myopic	agent	exp
tn006	l	l	planutilswap	soph	agent	exp
tn007	l	m	planutilswap	soph	agent	exp
tn008	m	l	planutilswap	soph	agent	exp
tn009	m	m	planutilswap	soph	agent	exp
tn010	l	l	planutilswap	resolute	agent	exp
tn011	l	m	planutilswap	resolute	agent	exp
tn012	m	l	planutilswap	resolute	agent	exp
tn013	m	m	planutilswap	resolute	agent	exp

4.1.4. Configurations: 14-22

Same as 5-12 but using MH preference during execution phase.

testn	brc	brt	planutil	strategy	pref	executil
tn014	m	m	none	myopic	mh	exp
tn015	l	l	planutilswap	soph	mh	exp
tn016	l	m	planutilswap	soph	mh	exp
tn017	m	l	planutilswap	soph	mh	exp
tn018	m	m	planutilswap	soph	mh	exp
tn019	l	l	planutilswap	resolute	mh	exp

tn020	l	m	planutilswap	resolute	mh	exp
tn021	m	l	planutilswap	resolute	mh	exp
tn022	m	m	planutilswap	resolute	mh	exp

4.1.5. Configurations: 23-40

Same as 14-22 but using ECOC-based utility rather than neoclassical utility during the execution phase. This is not expected to produce replanning since the ECOC thresholds are not used. They are defaulted to *ecoc-th=0.0* and *act-th= 0.0*.

testn	brc	brt	planutil	strategy	pref	executil
tn023	m	m	none	myopic	agent	ecoc
tn024	l	l	planutilswap	soph	agent	ecoc
tn025	l	m	planutilswap	soph	agent	ecoc
tn026	m	l	planutilswap	soph	agent	ecoc
tn027	m	m	planutilswap	soph	agent	ecoc
tn028	l	l	planutilswap	resolute	agent	ecoc
tn029	l	m	planutilswap	resolute	agent	ecoc
tn030	m	l	planutilswap	resolute	agent	ecoc
tn031	m	m	planutilswap	resolute	agent	ecoc
tn032	m	m	none	myopic	mh	ecoc
tn033	l	l	planutilswap	soph	mh	ecoc
tn034	l	m	planutilswap	soph	mh	ecoc
tn035	m	l	planutilswap	soph	mh	ecoc
tn036	m	m	planutilswap	soph	mh	ecoc
tn037	l	l	planutilswap	resolute	mh	ecoc
tn038	l	m	planutilswap	resolute	mh	ecoc
tn039	m	l	planutilswap	resolute	mh	ecoc
tn040	m	m	planutilswap	resolute	mh	ecoc

4.2. Test Series 2

In the next set of tests, re-planning is not only based on different bounds, preference order and decision strategies. It is also based on the emotional threshold of the agent. Here, all agent configurations use the resolute decision strategy, *ecoc()* expected utility during execution, and *planutilswap* plan utility. Different combinations of model attributes are used. First, model configurations use different bounds and preference order, either A or MH. Second, different ECOC and action thresholds are used to represent different agent characteristics. Some test numbers (t*estn*) will be post-fixed with letters (a, b, aa). These are tests that were added after the original order was generated to include *ecoc-th=0.1* and *act-th=0.1*.

4.2.1. Configurations: 41-116

For the following factors, permutations for each ecoc-th and act-th values are generated. This generates 92 tests in total, including additional ones post-fixed with letters, as mentioned above.

testn	brc	brt	planutil	strategy	pref	executil	ecoc-th	act-th
tn40	l	l	planutilswap	resolute	agent	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]
.	l	m	planutilswap	resolute	agent	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]
.	m	l	planutilswap	resolute	agent	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]
.	m	m	planutilswap	resolute	agent	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]
.	l	l	planutilswap	resolute	mh	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]
.	l	m	planutilswap	resolute	mh	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]
.	m	l	planutilswap	resolute	mh	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]
tn116	m	m	planutilswap	resolute	mh	ecoc	[0.1,0.2,0.3,0.4,0.6]	[0.1,0.3,0.5]

5. Analysis

The analysis performed in this report compares model performance based on true positive rates and false positive rates of models. A model's ability to accurately emulate actual trajectories is based on the mean absolute error (MAE) between the simulated and actual trajectory of clients.

Recall that not all replanning is triggered by the *ecoc-th* threshold. When a plan is not found within the *BR(C)* or *BR(T)* limit, the last goal in the list is deferred and a new search begins. Once a plan is successfully found and executed, the deferred goals are all retrieved and the process begins again. Hence, a low *BR(C)* or *BR(T)* may cause replanning without considering the *ecoc-th* threshold. The myopic and sophisticated strategies also perform replanning at every time step. The sophisticated strategy depends on BR(C) and BR(T) to build plans that are compared. The myopic strategy is not impacted by BR(C) or BR(T) and both are set to medium. Series 1 experiments are performed with *ecoc-th=0* and are only based on BR(C) and BR(T) and the strategy used.

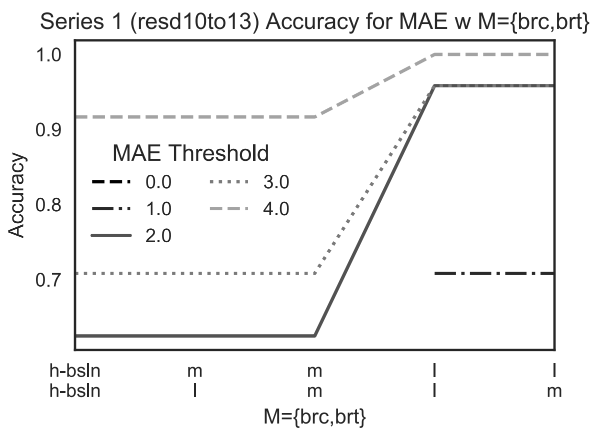
The MAE_M for tested models varies from 0.3 to 14. In the results below, analysis with MEP graphs was limited to MAE_M between 0.0 and 4.0.

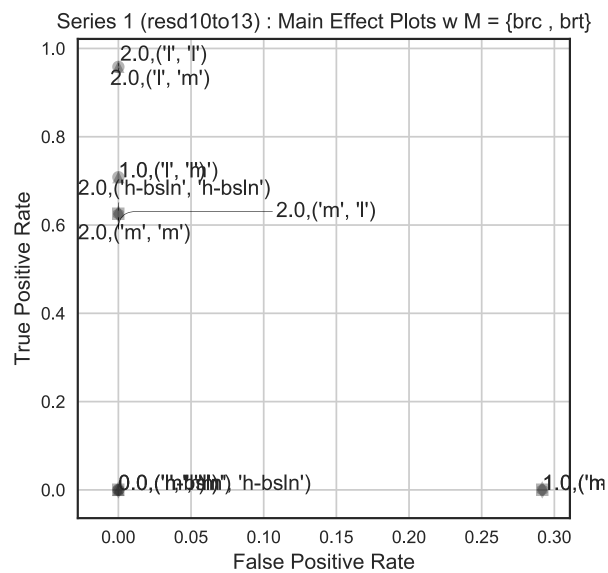
5.1. Series 1: Experiment Analysis

Hypothesis-1: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with bounded rationality limits than without.

Results 1.1) Baseline vs BR

Tests	*baseline, 10-13*
Grouping	*testn, brc, brt*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap*
strategy	*resolute, resolute-bsln (bsln for baseline)*
pref	*agent*
executil	*exp (neoclassical utility)*





Analysis:

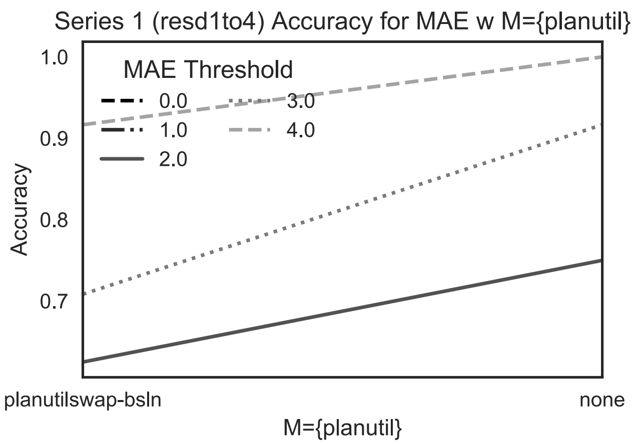
Looking at the accuracy graph, we see that MAE=1.0 only produces models with BR(C)=l. When MAE=2.0, models with BR(C)=l have the highest accuracy. Baseline (h-bsln) configuration is not distinguishable from configurations where BR(C)=m. Seems replanning due to BR(C) improves the model's accuracy.

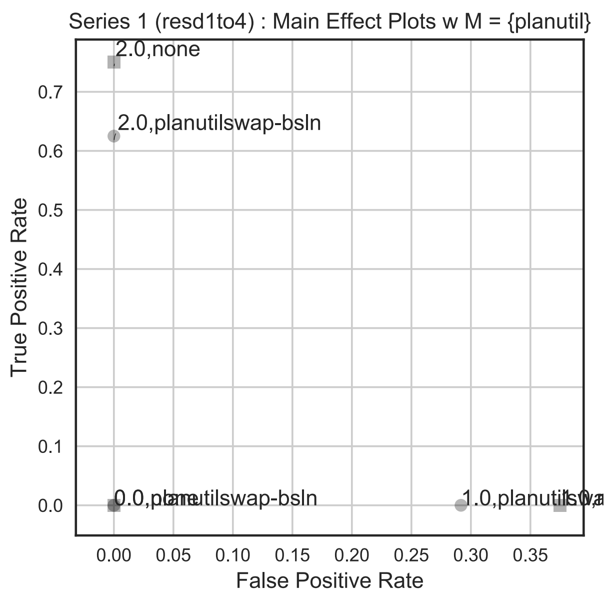
Viewing the Main Effect Plots graph, we see all combinations of the chosen factors for models with MAE $\leq$ 2.0. MAE = 2.0 has the best score. Models with BR(C)= *l* for low have the best TPR to FPR ratio. With MAE = 1.0, again models with BR(C) = *l* for low have the best TPR to FPR ratio. BR(T) has no impact on any models.

Hypothesis-2: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with plan utility maximization than without.

<u>Results 2.1) Baseline vs without utility maximization</u>

Tests	*baseline, 1-4*
Grouping	*planutil*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap-bsln, none*
strategy	*resolute-bsln, resolute*
pref	*agent (bsln only)*
executil	*exp (bsln only)*



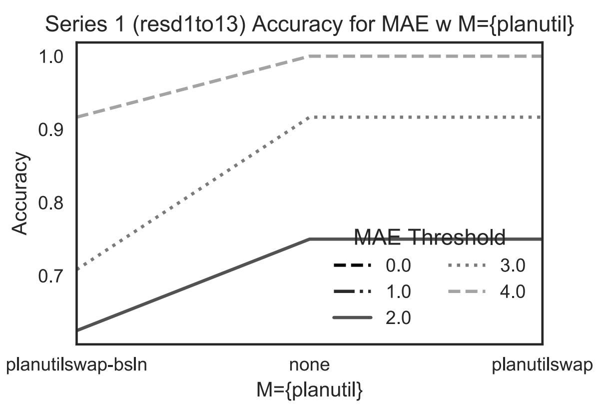


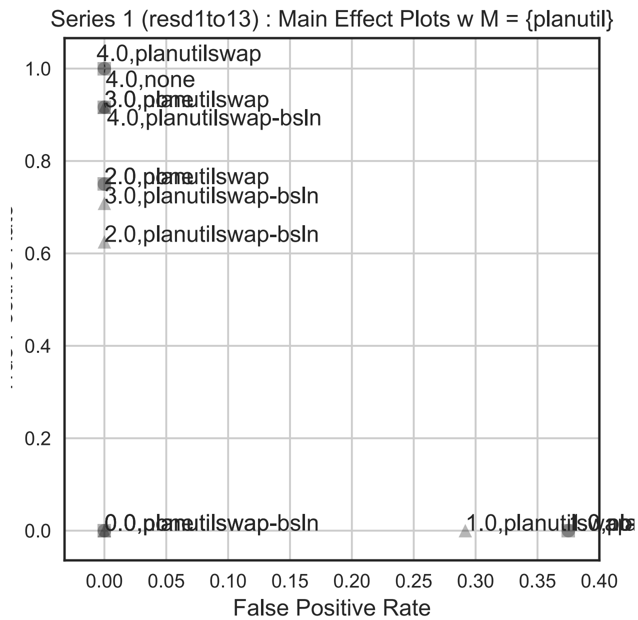
<u>Analysis:</u>

These configurations show that an MAE of at least 2.0 is needed to make any predictions using planutil only. These models are good at emulating real behavior to within 2 goals. When planutil=none, the first plan found is selected for execution. Baseline relies on planutil=planutilswap, which selects the plan with highest utility. Accuracy graph shows that some improvements exists when the first plan is chosen over baseline. Since tests 1-4 include BR(C) of low and high, the improvement is caused by replanning due to cognitive bounds. Baseline has no replanning. The increase in accuracy, however, is not significant.

Results 2.2) Baseline versus BR and planutil
To investigate the impact BR has on planutil by comparing results we review the following results.

Test	*baseline, 1-13*
Grouping	*planutil*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap=bsln, none, planutilswap*
strategy	*resolute-bsln, resolute*
pref	*agent*
executil	*exp*

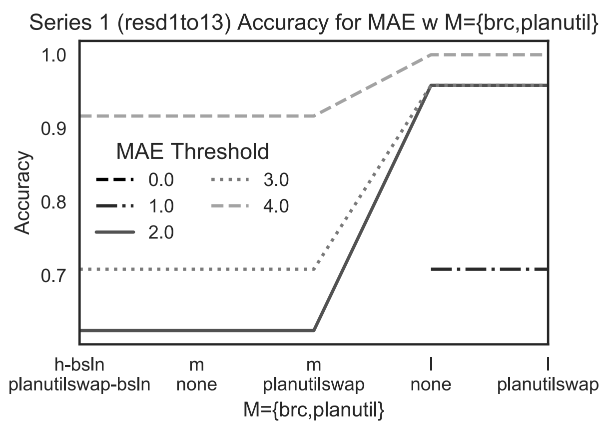


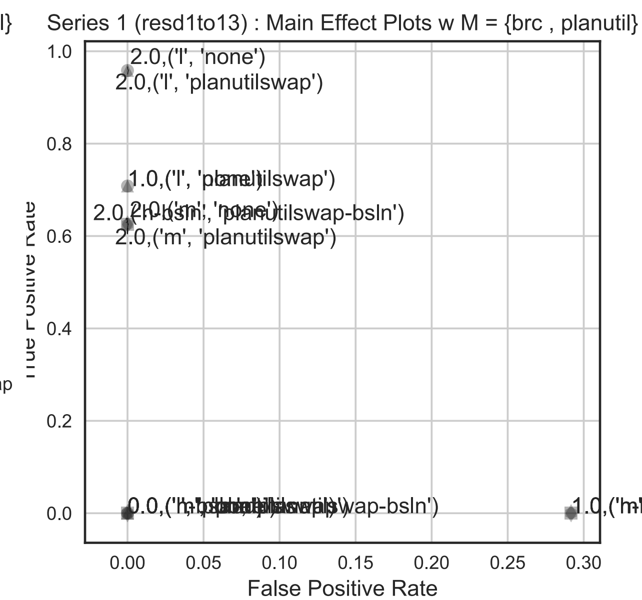


Analysis:
These tests combine configurations with different planutil (none and planutilswap being used). We see that no significant difference is observed, except between baseline and other tests. The cause of this is the main difference between baseline and the other two groups, mainly that baseline has no replanning, with high (h-bsln) bounds that the planner can find at least one plan that satisfies all goals. The other configurations require replanning due to bounds.

<u>Results 2.3) Baseline versus BR(C) and planutil</u>
To evaluate the impact BR(C), which so far has produced the lowest error, has on planutil, we group results based on these two factors.

Tests	*baseline, 1-13*
Grouping	*brc, planutil*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap=bsln, none, planutilswap*
strategy	*resolute-bsln, resolute*
pref	*agent*
executil	*exp*



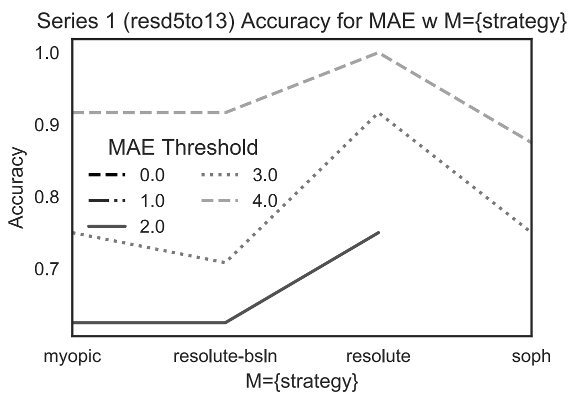


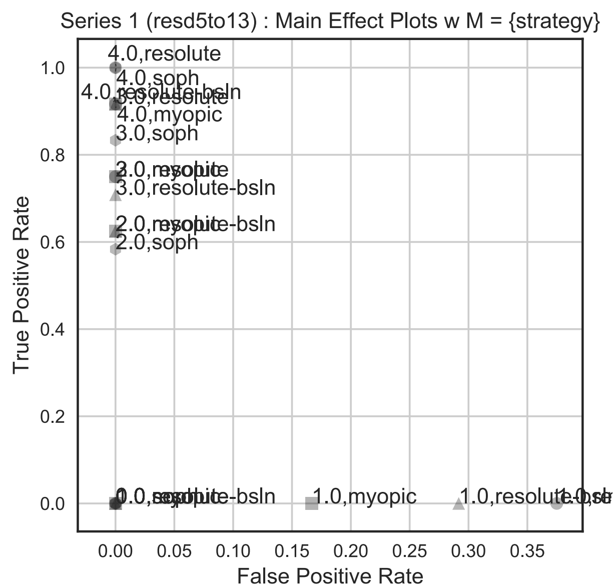
<u>Analysis:</u>
These tests are the same as in Results 2.2 but BR(C) was added to the grouping. We saw in previous tests that BR(C) was a distinguishing factor and test it here against planutil which was not. Reviewing the MEP results we see the highest accuracy and TPR is again due to BR(C) = *l* for low, rather than if plan utility is used or not.

Hypothesis-3: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with myopic and sophisticated search strategies than without.

<u>Results 3.1) Baseline versus strategy</u>

Tests	*baseline, 5-13*
Grouping	*strategy*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap=bsln, planutilswap*
strategy	*resolute-bsln, resolute, myopic, soph(isticated)*
pref	*agent*
executil	*exp*





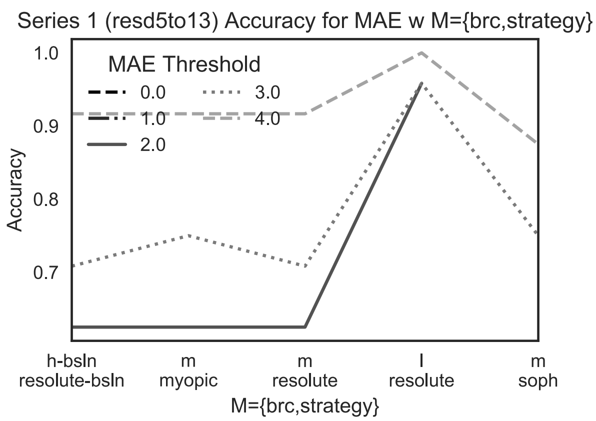
<u>Analysis:</u>

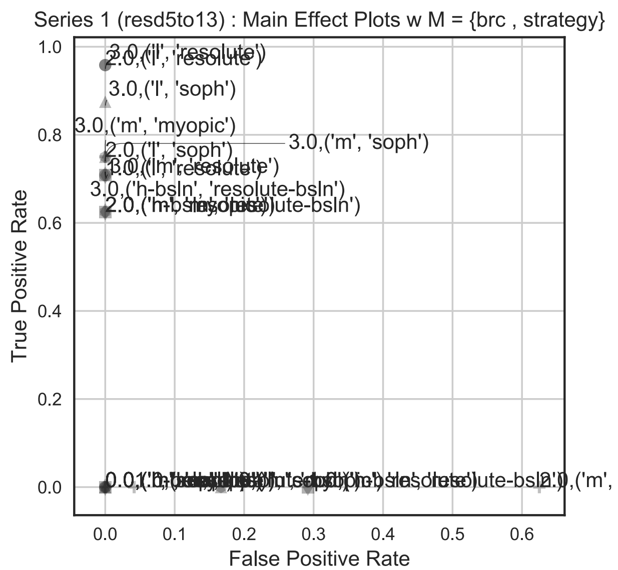
For MAE=2.0, the resolute strategy has a higher accuracy than myopic and resolute for baseline, although the accuracy is low, from around 0.6 to 0.7. From these results, we see that there is no significant difference between resolute versus myopic or sophisticated. Note again that baseline also uses resolute but with high bounds. Hence, the only difference between resolute and resolute-bsln is that resolute has replanning due to bounds.

Next we look at the impact BR(C) has on the error for each strategy.

<u>Results 3.2) Baseline versus BR and strategy</u>

Tests	*baseline, 5-13*
Grouping	*brc, strategy*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap=bsln, planutilswap*
strategy	*resolute-bsln, resolute, soph, myopic*
pref	*agent*
executil	*exp*





<u>Analysis:</u>

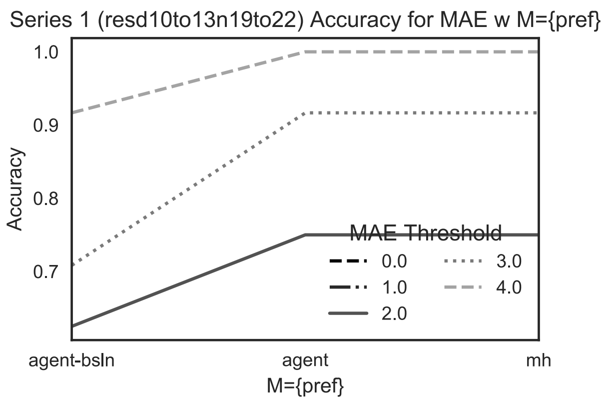
Here again we see that BR(C)=l is the biggest distinguishing factor in increasing accuracy. A resolute strategy with BR(C)=m has the same accuracy as other strategies. The MEP data indicates that TPR > 0.7 if BR(C) = l and strategy=resolute. From this result, we see that combining low BR(C) with a resolute strategy produces the best combination of TRP and FPR. Other configurations have MAE > 2.0. The myopic strategy does not attempt to build an entire plan for all goals, only one goal at a time, hence it was only tested with a medium BR(C).

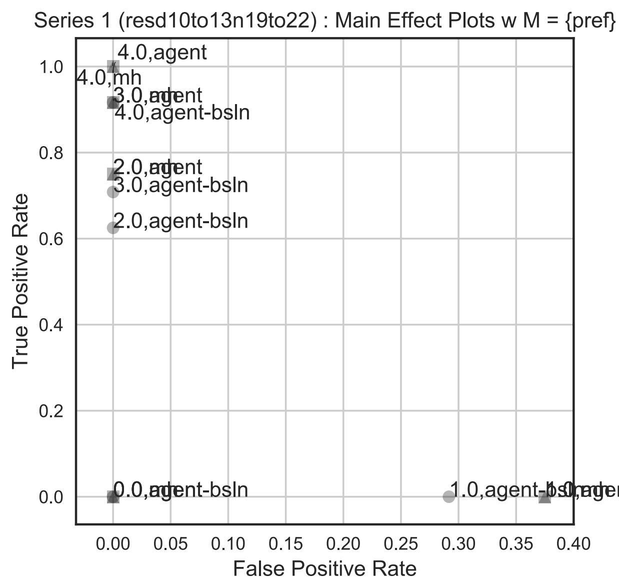
Hypothesis-4: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with Maslow's hierarchy as preferred goal ranking than without.

So far we have only used configurations with the agent's preferred order, where *pref=agent*. We now introduce Maslow's order for comparison, where *pref=mh*.

<u>Results 4.1) Baseline versus preferences</u>

Test	*baseline, 10-13, 19-22*
Grouping	*pref*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap-bsln, planutilswap*
strategy	*resolute-bsln, resolute*
pref	*agent, mh*
executil	*exp*





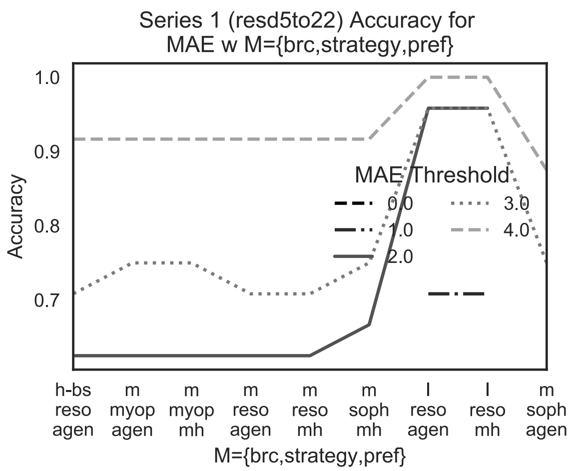
<u>Analysis</u>

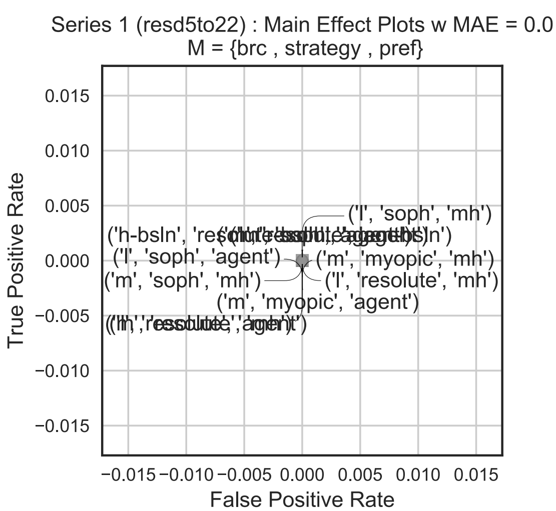
Here we see no difference between the two preference. Further analysis is required. This may be because the goals are already somewhat aligned with MH, action preconditions constrain possible plans to vary in order, or the cognitive and time bounds do not allow for enough iterations to find plans of a large variety.

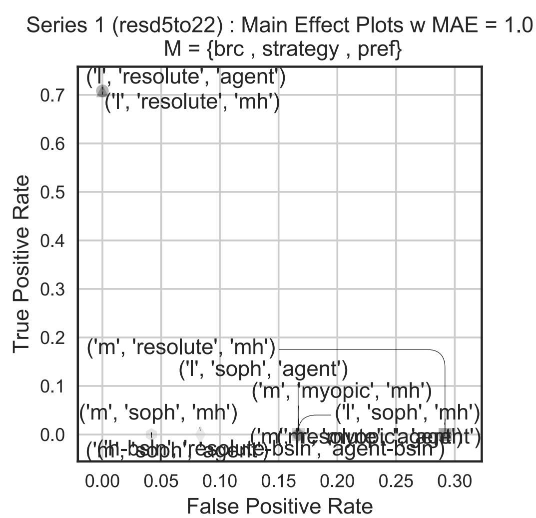
Note: Follow-up tests revealed that the 60-minute limitation on simulation run-time excluded agents with more goals that required longer plans. Longer plans produced more variations of plan which included more variations of goal order. Hence, the reason there is no significant difference between MH and agent goal ranking is due to the run time limit. See Section 3.6.2 of this report for more information.

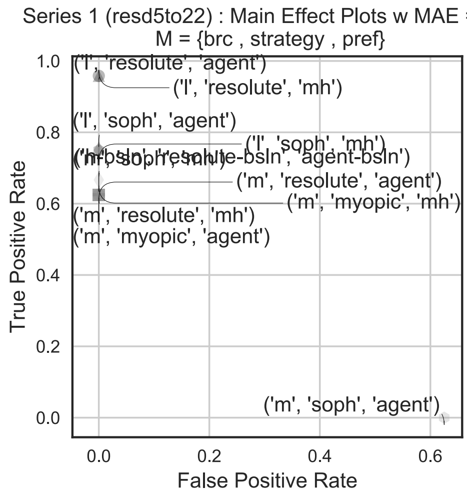
<u>Results 4.2) Baseline versus BR(C), strategy, and preferences</u>
This set of results group tests by the key factors influencing MAE and recall percentage.

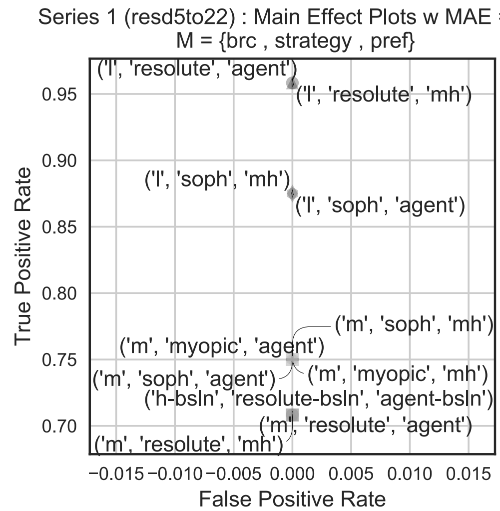
Test	*baseline, 5-22*
Grouping	*brc, strategy, pref*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap-bsln, planutilswap*
strategy	*resolute-bsln, resolute, myopic, soph*
pref	*agent, mh*
executil	*exp*

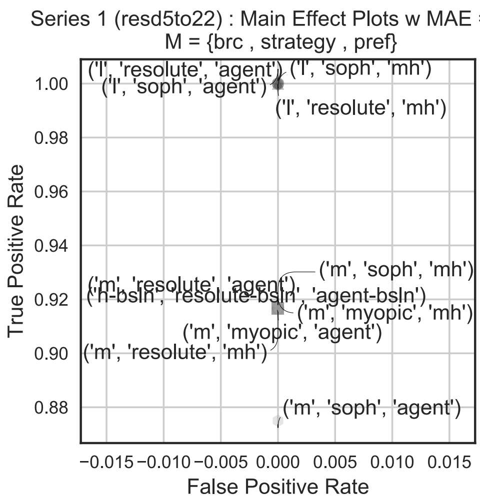












Analysis

The accuracy graph indicates again that BR(C)=l is the main contributor to a high accuracy score.

The MEP graphs are split by MAE. For MAE=0.0, there is no distinction between results and all no model was a perfect match. MEP =1.0 graph shows that models with BR(C)=l and resolute again had best results. All other models had very low TPR and high FPR.

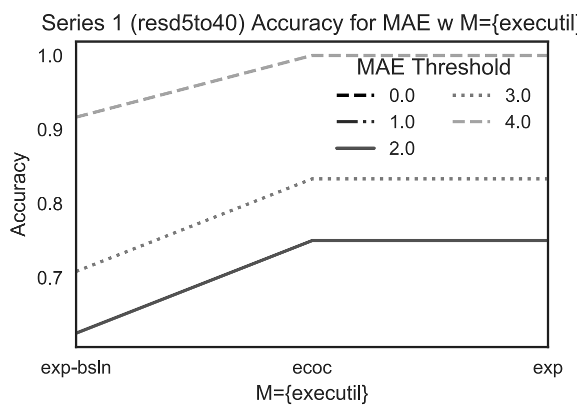
For MEP=2.0, all but the BR(C)=m and sophisticated strategy had improved results. The only model with the sophisticated strategy was for BR(C)=l. Based on previous results it seems highly likely that BR(C)=l is the main factor in the improvement. Based on these results, we say that given the replanning that occurs due to the low cognitive bound, preferences have no bearing on these smaller plans that are generated. Similarly, the preferences have no impact on the different strategies being applied by the agents. Like tests for Hypothesis 3, the resolute strategy has the lowest errors.

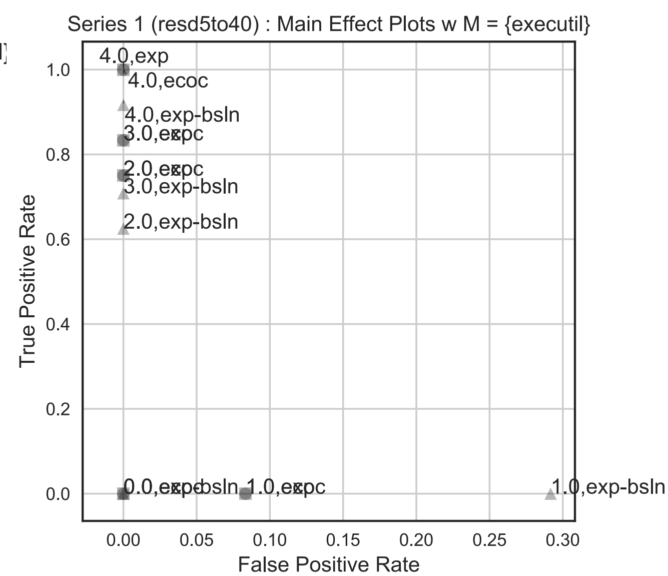
Hypothesis-5: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when maximizing ECOC expected utility than maximizing the neoclassical expected utility function.

The following results compare baseline against different configurations where executil is either the neoclassical utility function (exp) or ECOC-based utility function (ecoc). Based on previous results where the utility function did not play a distinguishing role that depend on the utility function, specifically pref and planutil, we don't expect executil to play a distinguishing role either. It is not until ECOC is used to trigger replanning with relevant thresholds will the ECOC utility function be relevant.

<u>Results 5.1) Baseline versus executil</u>
The following results only include configurations with:

Tests	*baseline, 5-40*
Grouping	*executil*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap-bsln, planutilswap*
strategy	*resolute-bsln, resolute, myopic, soph*
pref	*agent, mh*
executil	*exp, ecoc*

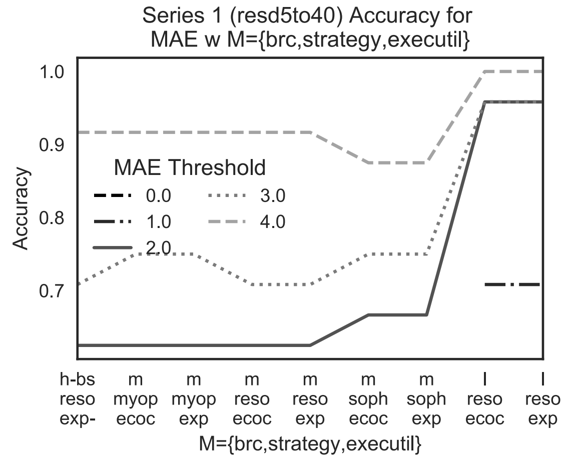


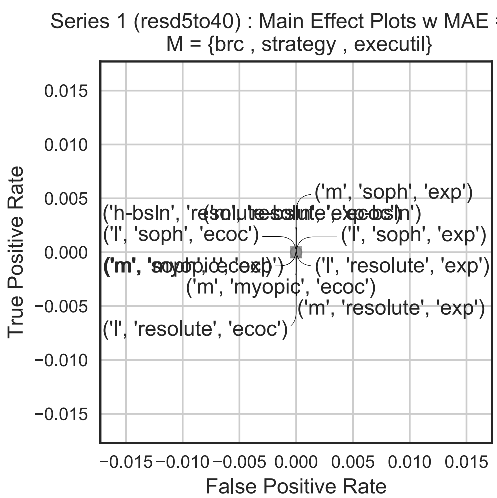


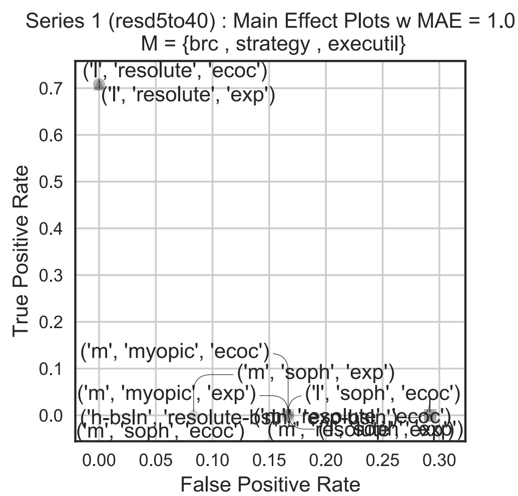
<u>Analysis</u>
As expected, there is no difference between the two utility functions exp and ecoc without thresholds. Models with MAE ≤ 1.0 have a TPR = 0.0, performing very poorly. The models with MAE ≥ 2.0, where TPR > 0.0, do not react to the executil factor. For this MAE range, the worst model is the baseline, where executil=exp-bsln. Models with exp and ecoc had no displayed no differences.

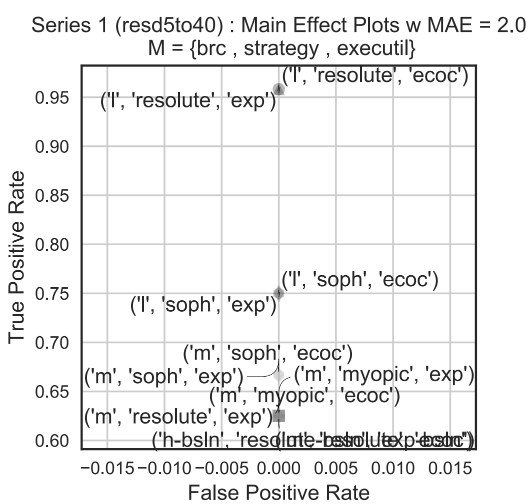
<u>Results 5.2) Baseline versus BR(C), strategy, executil</u>
To ensure the other factors contribute the same to each utility function, we group the results using three main factors considered until now, mainly BR(C), strategy, and executil.

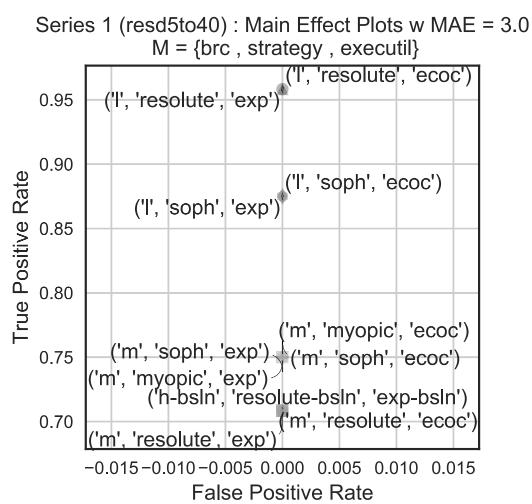
Tests	*baseline, 5-40*
Grouping	*brc, strategy, executil*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap-bsln, planutilswap*
strategy	*resolute-bsln, resolute, myopic, soph*
pref	*agent, mh*
executil	*exp, ecoc*

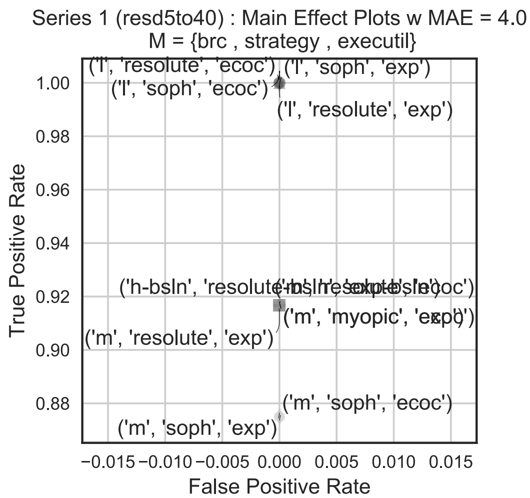












<u>Analysis</u>

Here we confirm that the utility functions executil=exp or ecoc do not impact accuracy or the TPR:FPR ratio. In the individual MEP graphs we see that each point is grouped by BR(C) and strategy. We also note that for MAE=1.0, models with BR(C)=l and resolute strategy have the best results, although the model is sensitive to these factors.

5.2. Series 1: Experiment Analysis Summary

The accuracy score for each configuration in Series 1 is shown below in Figure 5. Here we see the distinguishing factor being BR(C)=l. Independent of other factors, accuracy score is consistently higher.

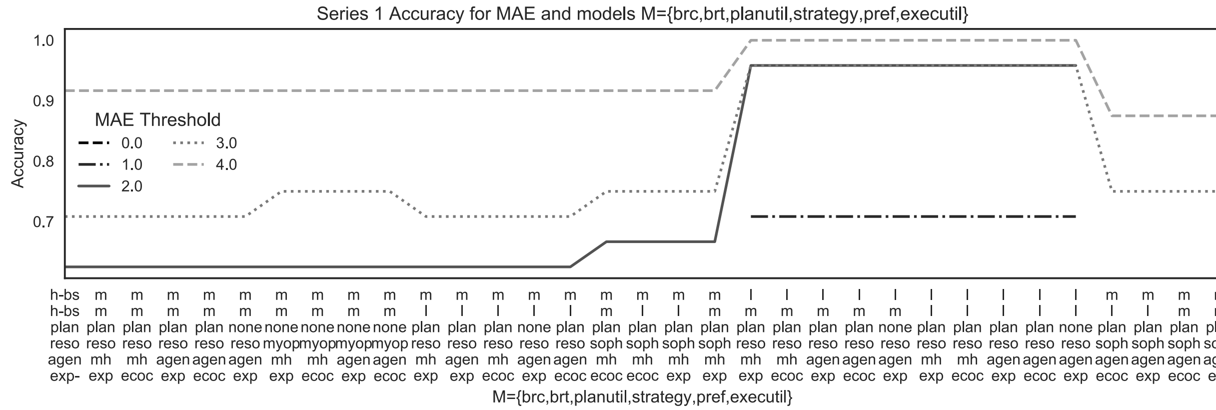


Figure 5. Series 1 MAE for each threshold, sorted by MAE threshold 2.0.

The grouped MAE graph in Figure 6 summarizes the key factors investigated in Series 1, where models are grouped by the distinguishable factors *BR(C), BR(T), strategy*, and *pref*. Best results for Series 1 are configurations where *BR(C)* is low and the *strategy* is resolute. *pref* is not a distinguishing factor. Hence, Figure 6 shows how different $\mathbb{M}$ configurations and their mean. The models have most stable performance where MAE $\leq$ 2.0. Where MAE > 2.0, outliers are seen. While the lowest value overall are BR(C)=l, it is more sensitive to outliers on the right hand side of the graph. BR(C)=m has higher overall mean model $MAE_{\mathbb{M}}$ but also a lower error for outliers.

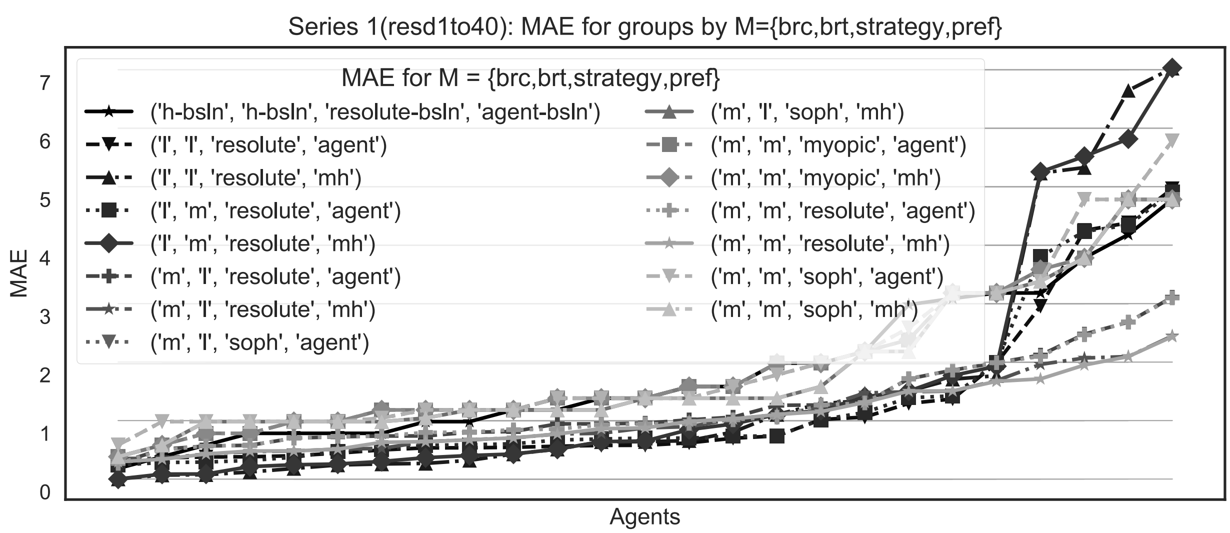


Figure 6. Series 1 summary MAE results.

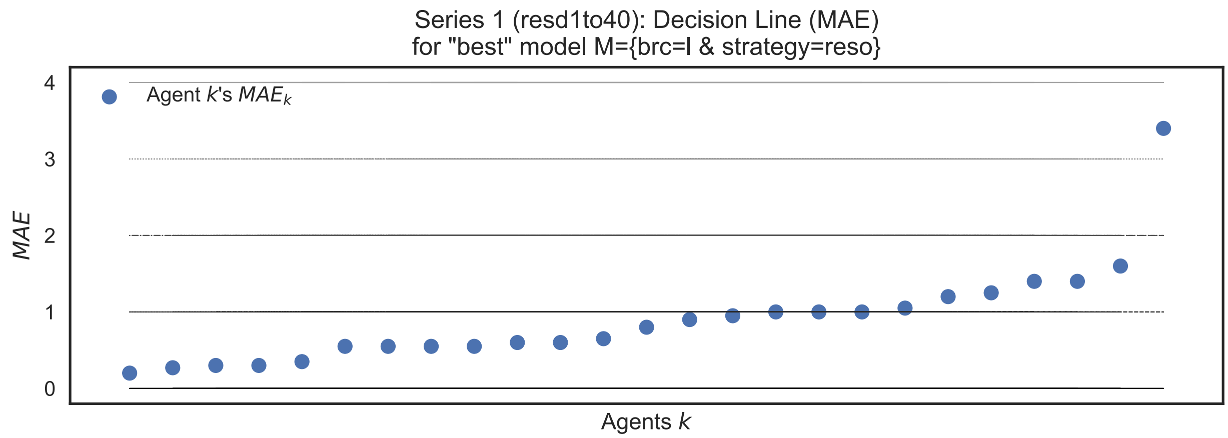


Figure 7. Series 1 best model MAEk for each agent k

In Figure 7, the MAEk scores for each agetn *k* are shown for model configurations where BR(C)=l and stratgy=resolute. Here we see that for most, except for one outlier, MAE < 2.0, and averages 1.0. Depending on the application requirements of the model, MAE=1.0 or MAE=2.0 can be used, with the lower MAE producing better results.

Next we analyze the individual configurations with Main Effect Plots to identify those combinations of factor s and values that produce the best results.

Main Effect Plots with MAE = 0.0

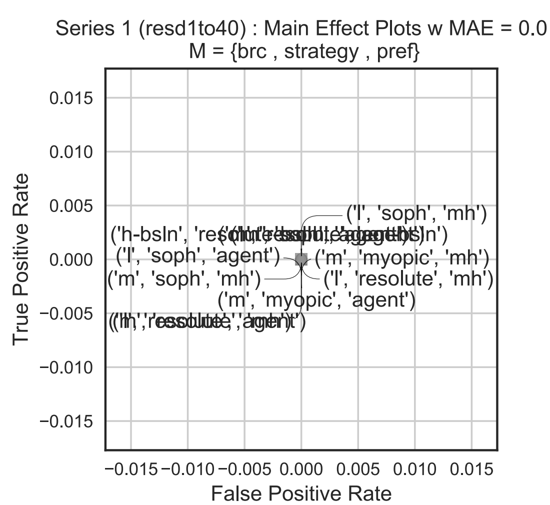


Figure 8. Series 1 summary MEP results with MAE = 0.0.

This MAE threshold identifies models that produce perfect matches. As the MEP graph indicates, no models were found.

Main Effect Plot with MAE = 1.0

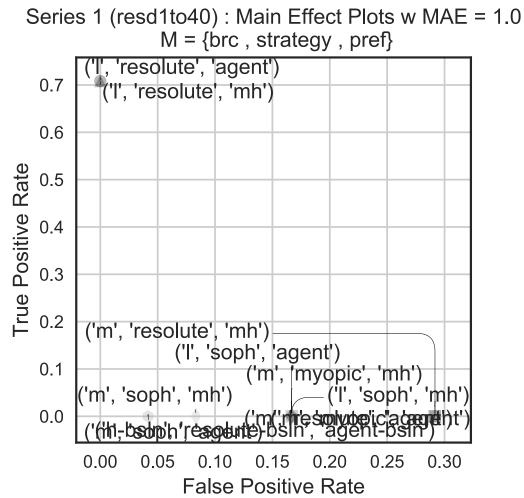


Figure 9. Series 1 summary MEP results with MAE = 1.0.

This MAE threshold is considered a good measure of a model's performance. From the main factors identified, a low BR(C) and the resolute strategy produce the best results.

Other models produce results with TRP = 0.0.

Main Effect Plot with MAE = 2.0

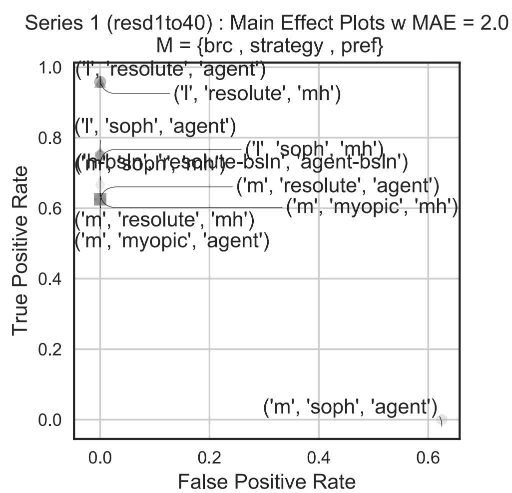


Figure 10. Series 1 summary MEP results with MAE = 2.0.

This MAE threshold is reasonable secondary measure of a model's performance. From the main factors identified, a low BR(C) and resolute strategy is again the best performing configuration.

The sophisticated strategy also performs well with a low BR(C), where TPR > 0.7. We also see medium BR(C) with myopic and resolute strategies appear above TPR=0.6. The reason for these is the frequency with which each configuration triggers replanning. The myopic strategy replans at every time step. Resolute strategy with BR(C)=m replans less often than with BR(C)=l. The sophisticated strategy replans at every step, but takes a cautious approach to planning. Hence, the lower BR(C) forces planning with less goals (that fit in a smaller plan). A sophisticated strategy with a medium BR(C) produces TPR=0.0 (bottom right corner). This indicates that just relying on the sophisticated strategy is not as important as a low BR(C).

Main Effect Plot with MAE = 3.0

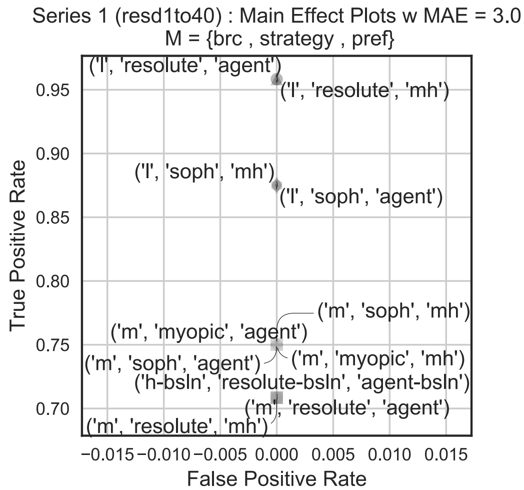


Figure 11. Series 1 summary MEP results with MAE = 3.0.

The MAE=3.0 is not considered a good measure of a model's performance. However, if an application can accommodate being off by at most 3 goals, it may be a reasonable error.

Main Effect Plot with MAE=4.0

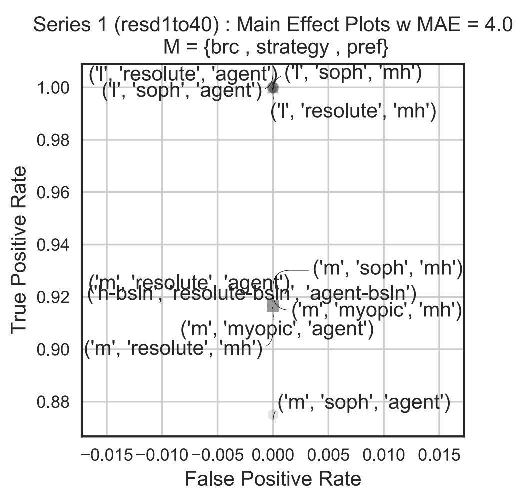


Figure 12. Series 1 summary MEP results with MAE = 4.0.

The MAE=4.0 threshold is not considered a good measure of a model's performance. However, all models achieve a TPR > 0.85 with FPR=0.0. If an application is not concerned with being off by at most 4 goals, this may be a sufficient error threshold.

5.3. Series 2 Experiments

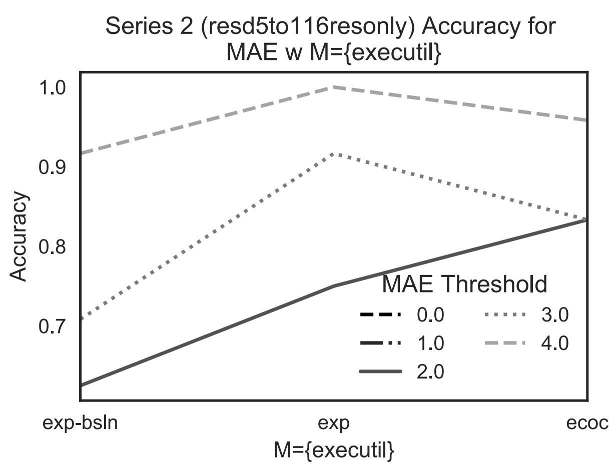
For the last set of configurations, we introduce the ECOC thresholds that can trigger replanning independently from the cognitive bounds, mainly *ecoc-th* and *act-th*. For these tests, some factors are held static. Only resolute strategy is used, while myopic and sophisticated strategies are omitted. The agent is assumed to maximize their utility, hence only planutilswap utility is used, and none is omitted. Finally, previous tests used ECOC utility function but replanning was not triggered using the utility. It was only triggered due to bounds. The ECOC tests included here from Series 1 are identified with threshold values of *ecoc-th*=0.0 and *act-th*=0.0. Also, only those Series 1 tests were included that used the resolute strategy to align with Series 2 tests.

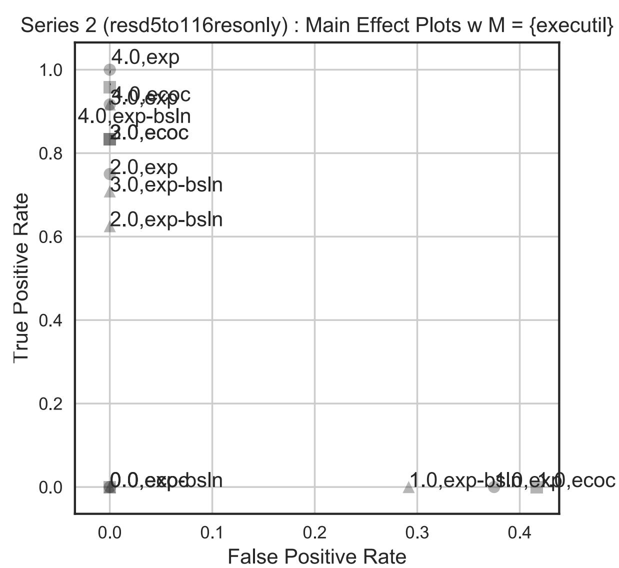
Hypothesis-6: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when replanning based on ECOC threshold than just bounded rationality limits.

<u>6.1) Baseline versus executil with ECOC-based replanning</u>

Tests *baseline, all tests from previous sections with resolute strategy (10-13, 19-22, 28-31, 37-40) new tests (41-116; omittings 65-68 which did not finish).*

Grouping *executil*
BR(C) *h-bsln, m, l*
BR(T) *h-bsln, m, l*
planutil *planutilswap-bsln, planutilswap*
strategy *resolute-bsln, resolute*
pref *agent, mh*
executil *exp-bsln, exp, ecoc*
ecoc-th *[0.0, 0.1, 0.2, 0.4, 0.6]*





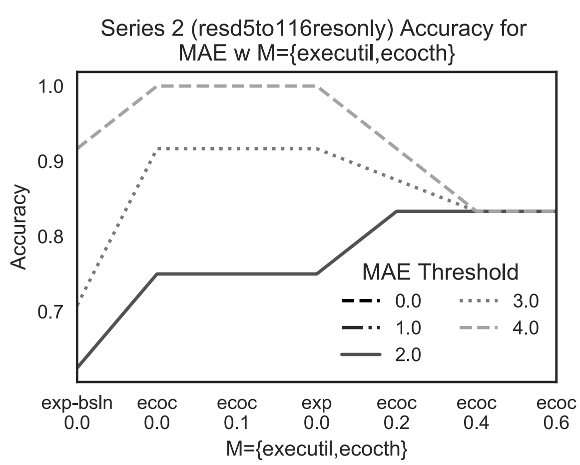
Analysis

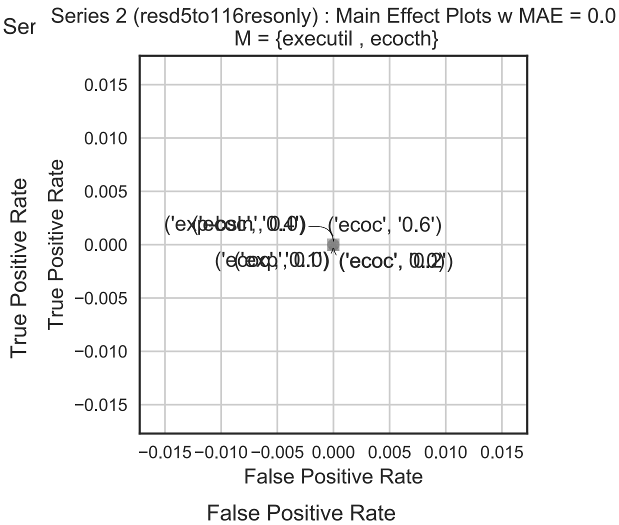
The Accuracy graph shows that executil=ecoc has a slight advantage over executil=exp. Both have higher accuracy than baseline. The MEP graph indicates that for each MAE threshold, the baseline model has the lowest TPR. Hence, some form of replanning is required to produce a better emulation model. The remaining analysis will answer whether the ecoc-th threshold is a better replanning trigger than a low BR(C) and the resolute strategy.

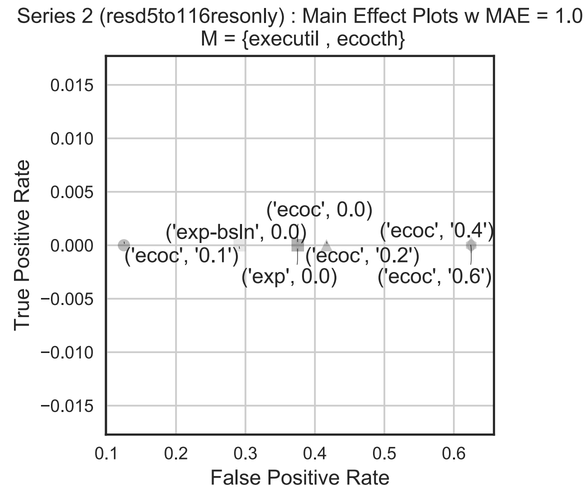
6.2) Baseline versus ecoc-th

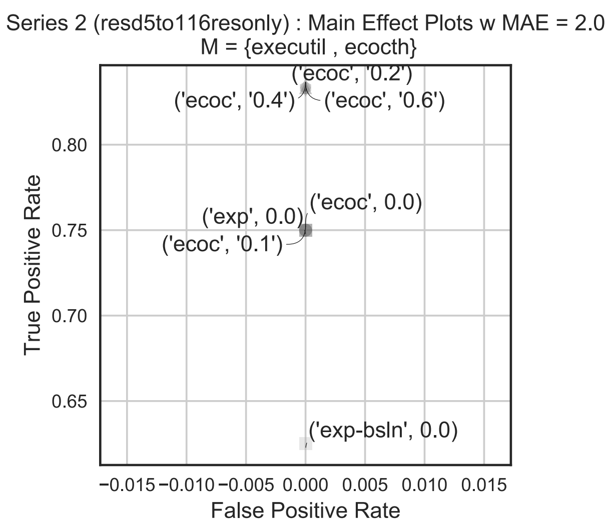
To investigate the impact of ECOC has on replanning, the following analysis groups test results on executil and ecoc-th. ECOC-based replanning is used when ecoc-th > 0.0.

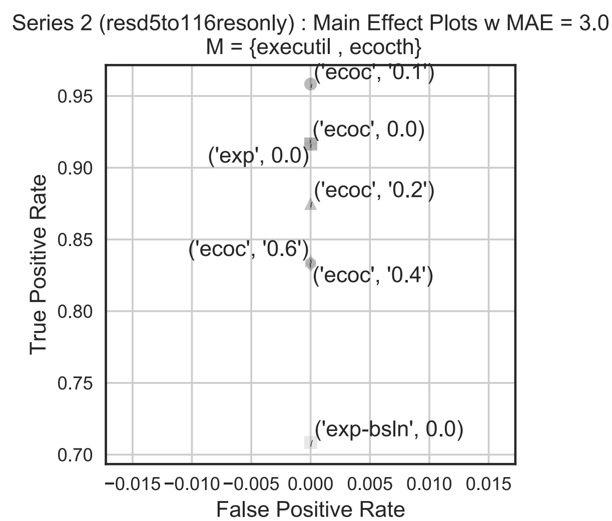
Tests	*baseline, all tests from previous sections with resolute strategy (10-13, 19-22, 28-31, 37-40) new tests (41-116; omittings 65-68 which did not finish).*
Grouping	*executil, ecoc-th*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap=bsln, planutilswap*
strategy	*resolute-bsln, resolute*
pref	*agent, mh*
executil	*exp-bsln, exp, ecoc*
ecoc-th	*[0.0, 0.1, 0.2, 0.4, 0.6]*











<u>Analysis</u>

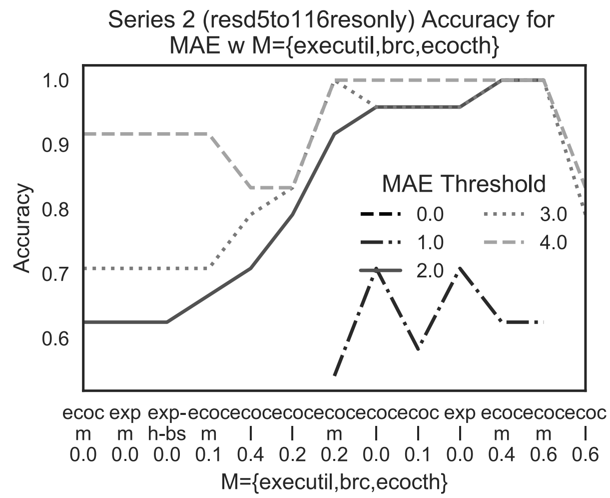
The accuracy graph shows that baseline is again the lowest scoring model. Where ecoc-th=0, there is no difference between exp or ecoc expected utility. Accuracy is increased when higher ecoc-th levels are used. Specifically, where ecoc-th ≥ 0.2 accuracy is above 0.8.

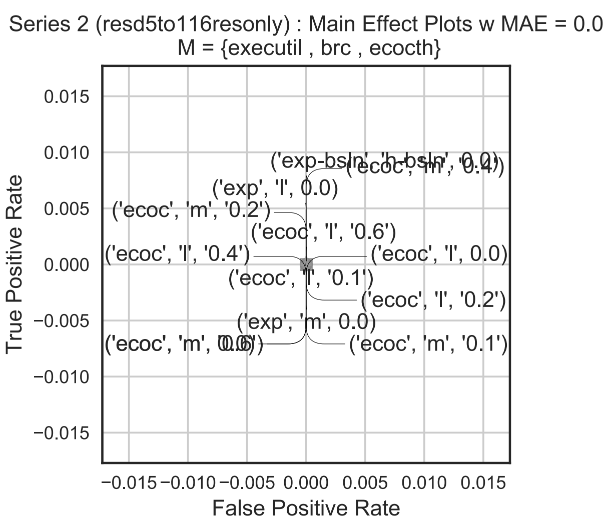
By looking at the MEP graph for MAE=2.0, executil=ecoc with ecoc-th ≥ 0.2 produce the highest TPR at 0.84 with FPR=0.0. The execution utility functions exp and ecoc with ecoc-th < 0.2 have TPR=0.0. These results are comparable to the best results from Series 1 in results 4.2 which were based on BR(C) and resolute strategy.

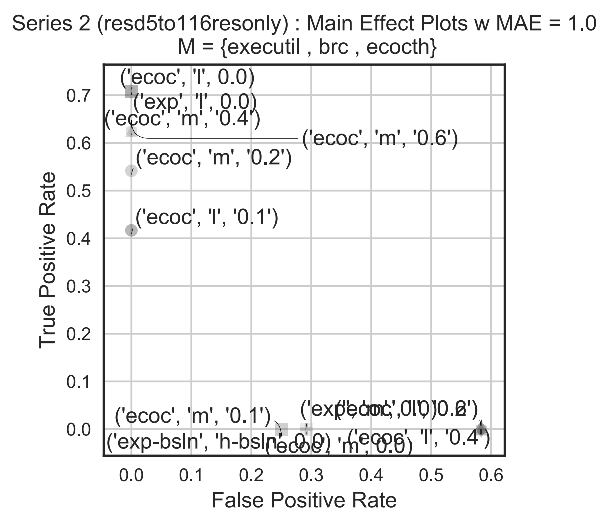
6.3) Baseline versus ecoc-th and BR(C).

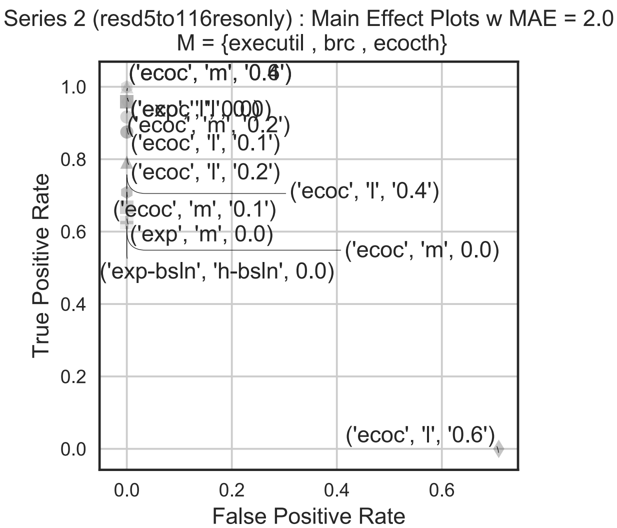
In previous analysis for Hypothesis 1 to 5 it was observed that a low BR(C) produces best results with the resolute strategy, as replanning is triggered due to cognitive limitations being reached, rather than myopic or sophisticated strategies that reevaluate plan utility at every time step. We now turn our attention to evaluating BR(C) versus ecoc-th.

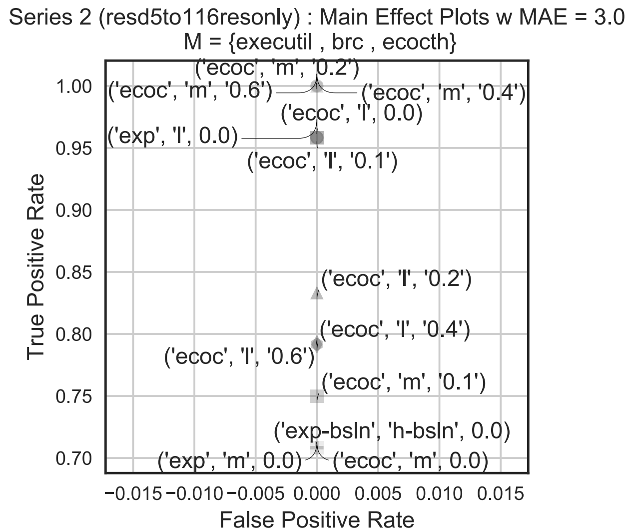
Tests	*baseline, all tests from previous sections with resolute strategy (10-13, 19-22, 28-31, 37-40) new tests (41-116; omittings 65-68 which did not finish).*
Grouping	*executil, BR(C), ecoc-th*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap=bsln, planutilswap*
strategy	*resolute-bsln, resolute*
pref	*agent, mh*
executil	*exp-bsln, exp, ecoc*
ecoc-th	*[0.0, 0.1, 0.2, 0.4, 0.6]*

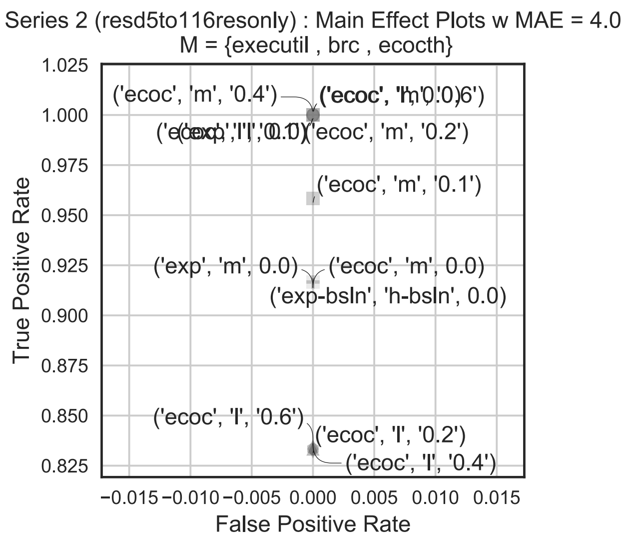












<u>Analysis</u>

The accuracy graph shows that accuracy is dependent on a combination of BR(C) and ecoc-th. Accuracy is high when either BR(C)=l and ecoc-th < 0.2, or BR(C)=m and ecoc-th ≥ 2.0. These tests are the first to show these discrete groups as contributing to a high accuracy score with different characteristics.

Looking at the MEP graph for MAE=1.0, we see that the best results, with TPR=0.7, are for models with a low BR(C), ecoc-th=0.0, and either the exp or ecoc utility functions. This indicates that like in Series 1, the best results are due to the low BR(C) limit.

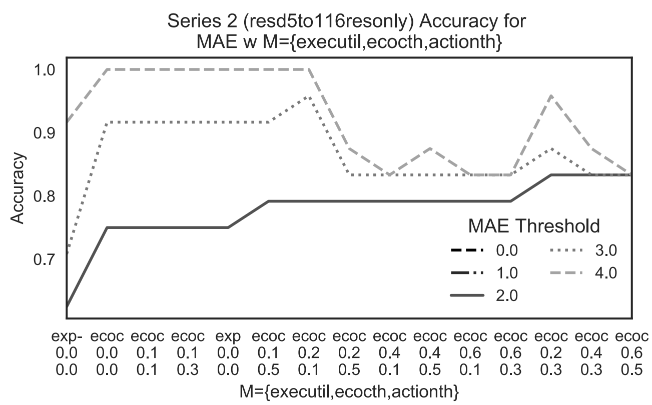
For the MEP graph with MAE=2.0 we see that the best result is for the model with ecoc-th=0.6 and medium BR(C), producing TPR=1.0 and FPR=0.0. These are followed closely by models with BR(C) and ecoc-th=0.0, as observed at the MAE=1.0 threshold. This indicates that at MAE=2.0, ecoc-th is playing a bigger role in replanning than BR(C) which is at medium.

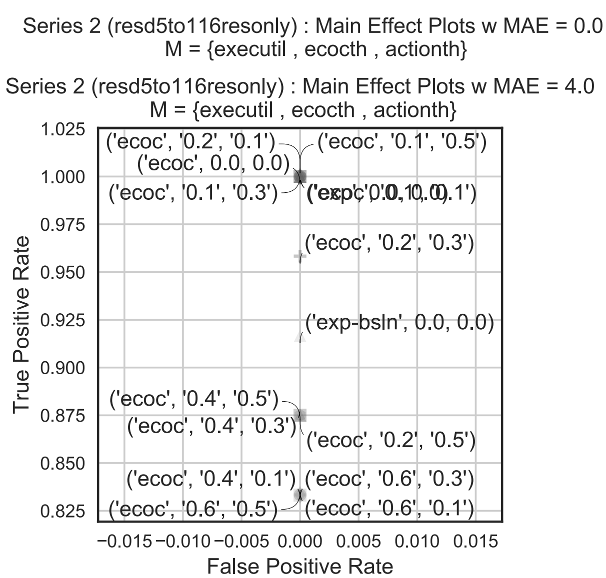
MAE > 2.0 display similar results with higher TRP but with less sensitivity.

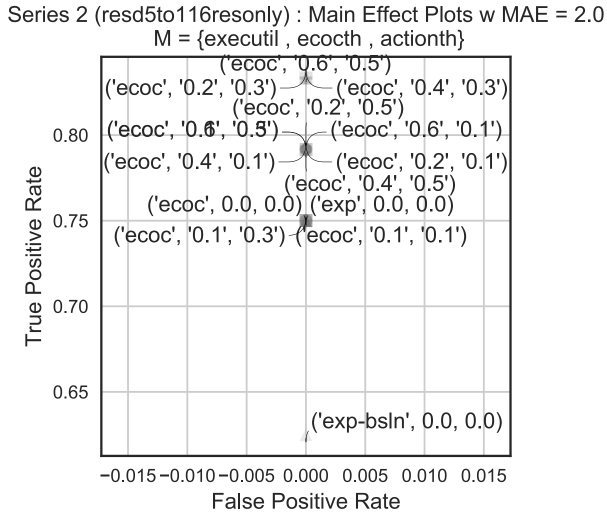
<u>6.4) Baseline versus executil, ecoc-th and act-th</u>

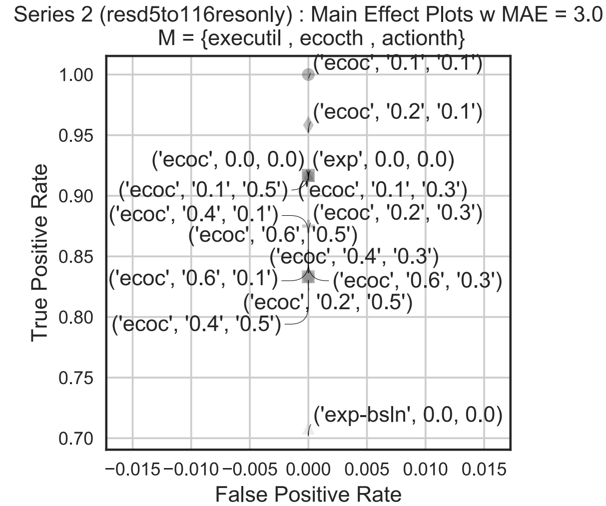
For the final analysis, we evaluate the action threshold act-th has on the results. We contrast them with ecoc-th as the two factors work together when ECOC-based replanning is triggered.

Tests	*baseline, all tests from previous sections with resolute strategy (10-13, 19-22, 28-31, 37-40) new tests (41-116; omittings 65-68 which did not finish).*
Grouping	*executil, ecoc-th, act-th*
BR(C)	*h-bsln, m, l*
BR(T)	*h-bsln, m, l*
planutil	*planutilswap=bsln, planutilswap*
strategy	*resolute-bsln, resolute*
pref	*agent, mh*
executil	*exp-bsln, exp, ecoc*
ecoc-th	*[0.0, 0.1, 0.2, 0.4, 0.6]*
act-th	*[0.0, 0.1, 0.3, 0.5]*









<u>Analysis</u>

In the final results we evaluate the impact action-th has on the results. The accuracy graph shows that there are small increases in accuracy if action-th values are higher. The increases, however, are not significant.

At MAE=2.0, the action-th does provide some improvements to the models where ecoc-th ≥ 0.2 with action-th ≥ 0.3. However, these are not better than improvements over medium and low BR(C) provides the models where to ecoc-th ≥ 0.2.

5.4. Series 2: Experiment Analysis Summary

The objective of Series 2 tests was to identify the impact ECOC-based replanning has on the error metric MAE. In this final summary section we summarize Series 2 results and contrast them with Series 1 results.

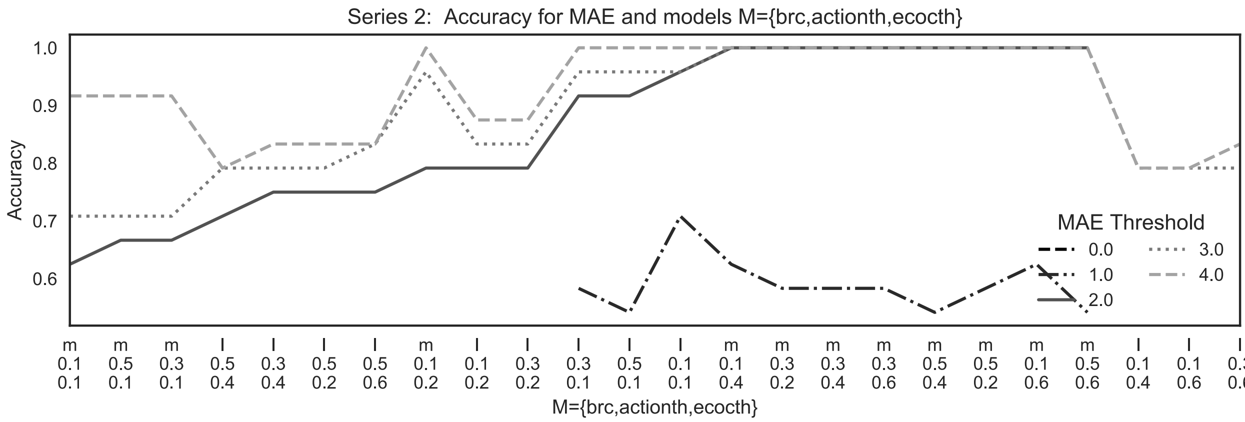


Figure 13. Series 2 MAE for each threshold, sorted by MAE threshold 2.0.

The accuracy score for each configuration in Series 2 is shown in Figure 13. Here we see the distinguishing factor being BR(C)=m with an ecoc-th ≥ 0.2. Models with BR(C)=l with ecoc-th ≥ 0.0 and action-th=0.1 produce the next highest accuracy. Since action-th is not deemed significant, this analysis concludes that certain combinations of BR(C) and ecoc-th produces the best models. Experiment 6.3 results highlighted the following relationship: accuracy is high when either BR(C)=l and ecoc-th < 0.2, or BR(C)=m and ecoc-th ≥ 0.2.

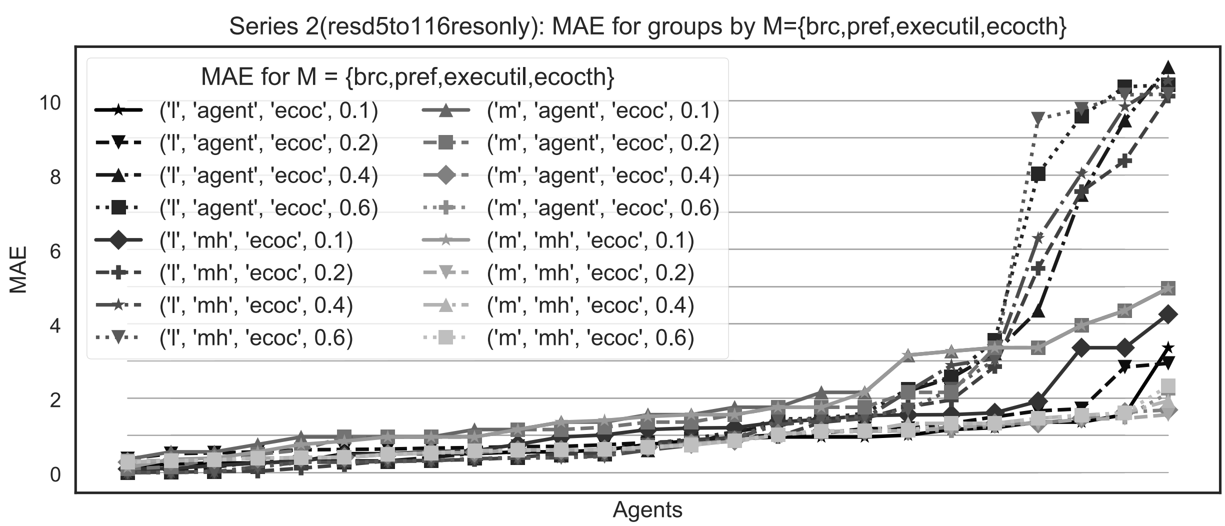


Figure 14. Series 2 best results using M={brc, pref, executil, ecocth}.

Figure 14 shows different model $\mathbb{M}$ configurations and their mean $MAE_{\mathbb{M}}$ scores, where models are grouped by *BR(C)*, *pref*, *execu*, and *ecoc-th*, Similarly to the best model in Series 1, where BR(C)=l, the models have most stable performance where MAE ≤ 2.0. Again, where MAE > 2.0, outliers are seen. While the lowest value overall are BR(C)=l, it is more sensitive to outliers on the right hand side of the graph. BR(C)=m has a lower mean model $MAE_{\mathbb{M}}$ as well as lower error for outliers.

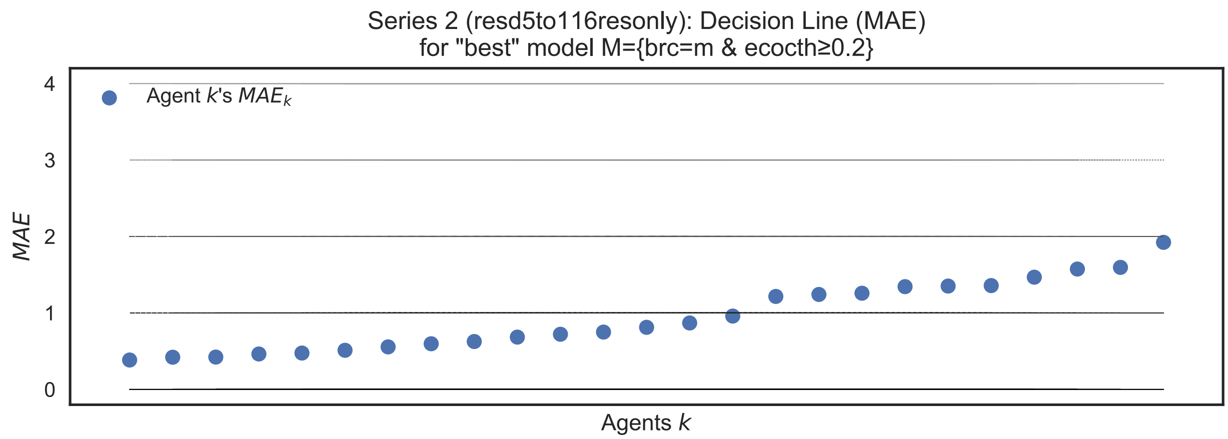


Figure 15. Series 2 best model MAE_k for each agent k

In Figure 15, the MAE_k scores for each agent *k* are shown for model configurations where BR(C)=m and ecoc-th ≥ 0.2. Here we see that all agents for this model have $MAE_k \leq 2.0$, and averages 1.0. Depending on the application requirements of the model, MAE=1.0 or MAE=2.0 can be used, with the lower MAE producing better results.

We finish this analysis by noting that in Series 1, models without ecoc-th had best results when BR(C) was included. However, results with TPR > 0.7 relied on a low BR(C) and resolute strategy. These models as well as those in Series 2 share the resolute strategy. However, Series 2 introduces ecoc-th. Introducing ecoc-th allows the models to be more resilient to changes in BR(C) by producing models with both low and medium BR(C) and TPR > 0.7.

We can conclude the analysis by stating that the results show that that combing BR(C) with ecoc-th improves the results while increasing the fidelity of the model.

6. Evaluation

In this section, each set of experiments are evaluated to identify whether each hypothesis was confirmed or denied. Determining whether a model is sufficient is based on two metrics. First is the accuracy of the model that indicates the model's ability to successfully identify a match between actual and simulated trajectories. The second is an MAE threshold that defines what is considered a "match." Different MAE thresholds were used and accuracy of each model evaluated.

6.1. Series 1 Evaluation

Figure 16 presents the accuracy of different $\mathbb{M}$ configurations at different MAE thresholds for Series 1 experiments. The models along the horizontal axis are sorted by their accuracy score for MAE thresholds of 2.0.

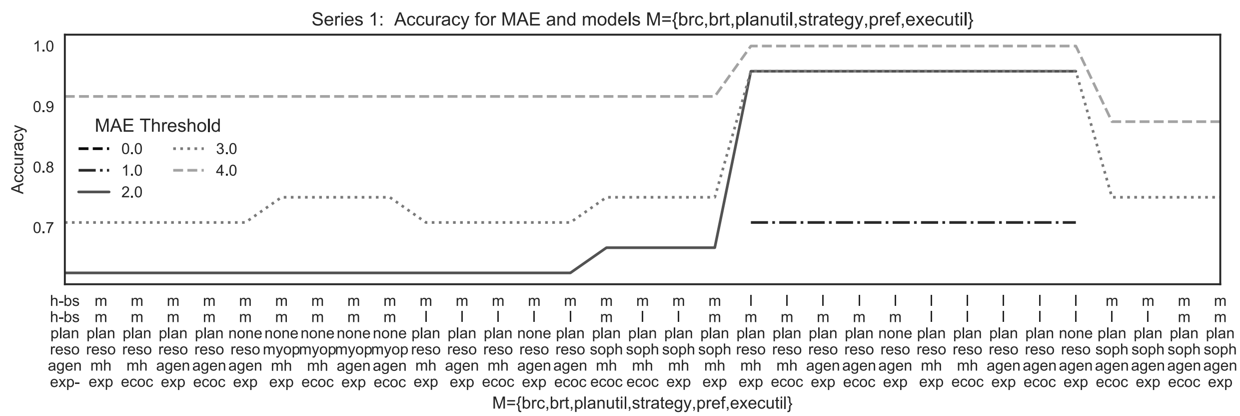


Figure 16. Series 1 MAE for each threshold, sorted by MAE threshold 2.0.

With an MAE threshold of 1.0, we see only models M with BR(C)=l (low) and strategy=resolute produced results that matched actual trajectories. However, the highest accuracy achieved was 0.7 for these models. With MAE threshold of 2.0, these same models simulate trajectories that match actual trajectories with accuracy of 0.95. In fact, these models have the highest accuracy at this MAE threshold. This result indicates that a low BR(C) and resolute strategy are the best factors for emulating actual clients. The resolute strategy itself is not sufficient, since the baseline model, identified by BR(C)=h-bsln (shortened to h-bs in the graph), has low scores. The only distinguishable feature of models with highest accuracy is the low BR(C).

The main takeaway from Series 1 results is that some form of replanning is required to create a good match of human-like behaviour for selected clients from the CHF-HF dataset. Also, it is not sufficient to force replanning at every time step by using the myopic or sophisticated strategy. Instead, a combination of a resolute strategy and a low BR(C) ensures that shorter partial plans are executed that satisfy a subset of goals per execution cycle.

The results for Series 1 experiments have direct implications for hypotheses 1 to 5.

Hypothesis-1: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with bounded rationality limits than without.

The baseline model configuration represents a rational agent in the neoclassical sense. It has high bounds, uses the neoclassical utility function (execu=exp) and the agent's preferred goal ranking (pref=agent). As demonstrated in Figure 16, baseline is in the group of models with the lowest accuracy for all MAE thresholds.

The models with a low BR(C) had the highest accuracy for all MAE threshold. The time bound BR(T) along with other factors did not seem to impact accuracy in any significant way. Hence, hypothesis 1 is confirmed that bounded agents produce a better emulation than those without, specifically those that have a low cognitive bound.

Hypothesis-2: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with plan utility maximization than without.

There is no significant difference between models that maximize utility (planutil=planswaputil; shortened to plan on the graph) versus those that do not (planutil=none). This is a result of computational limitations placed on the experiments, as discussed in section 7.1.4.

Hence, no conclusion can be made and hypothesis 2 is denied.

Hypothesis-3: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with myopic and sophisticated search strategies than without.

It is difficult to compare performance of models that used the resolute strategy to those that used either myopic or sophisticated. Computing limitations prevented models with sophisticated strategy and BR(C)=l to finish execution, and were excluded from the result. Models with the myopic strategy were not impacted by bounded cognition since only immediate actions were evaluated and there was no need to create a large search tree.

Two observations can be made from these results. First, models with the resolute strategy perform better than those with myopic strategies. Second, models with the sophisticated strategy require higher BR(C) bounds or longer computation time than either the resolute or myopic strategies. Combining both observations, the resolute strategy has the best performance within the computational limitations. The myopic strategy had more completed plans within the agents' bounds. Also, the sophisticated strategy had the worst performance of all three strategies. These results also show that replanning due to a low BR(C) rather than due to myopic or sophisticated strategies produces results with higher accuracy.

Hence, hypothesis 3 is denied, and better performance is achieved with the resolute strategy over myopic and sophisticated, especially when combined with a low cognitive bound.

Hypothesis-4: Seemingly "irrational" behaviour can be emulated using a rational reasoner better with Maslow's hierarchy as preferred goal ranking than without.

There is no significant difference between models that use Maslow's hierarchy (pref=mh) versus those that do not (pref=agent). This again is a result of computational limitations placed on the experiments, as discussed in section 7.1.4.

Hence, no conclusion can be made and hypothesis 4 is not confirmed or denied.

Hypothesis-5: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when maximizing ECOC expected utility than maximizing the neoclassical expected utility function.

There is no significant difference between models that use neoclassical utility function (executil=exp) versus those that use ECOC utility function (executil=ecoc). This again is a result of computational limitations placed on the experiments, as discussed in section 7.1.4.

Hence, no conclusion can be made and hypothesis 5 is not confirmed or denied.

6.2. Series 2 Evaluation

Figure 17 presents the accuracy of different M configurations at different MAE thresholds for Series 2 experiments. The models along the horizontal axis are again sorted by their accuracy score for MAE thresholds of 2.0. All models in Series 2 rely on strategy=resolute, planutil=planswaputil, and ECOC utility function. These are omitted from the horizontal axis. The time bound BR(T) was found to not be significant and is also omitted. The cognitive bound BR(C) along with action and ECOC thresholds action-th and ecoc-th are included.

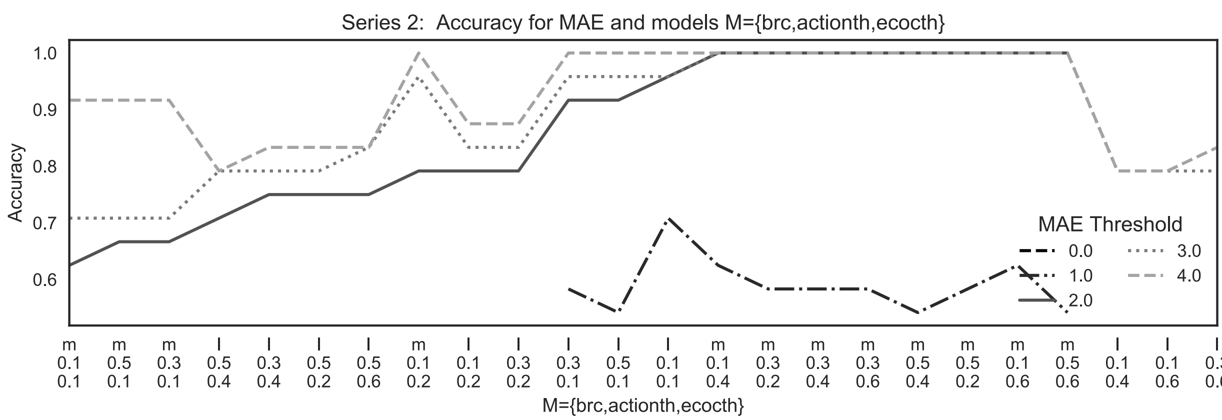


Figure 17. Series 2 MAE for each threshold, sorted by MAE threshold 2.0.

Like in Series 1, with an MAE threshold of 1.0, we see a partial list of models that were matched and produced an accuracy score. These are split into two groups, where BR(C)=l (low) and where BR(C)=m (medium). Where BR(C)=l, ecoc-th has a low value of 0.1, while for BR(C)=m the threshold ecoc-th has values greater than 0.1. The action threshold action-th has no significant impact on accuracy.

Not surprisingly, when the MAE threshold is 2.0 more models have matches and are visible on the graph. The same pattern is found as discussed in the previous paragraph. Models with BR(C)=l and lower ecoc-th have lower accuracy while models where BR(C)=m and ecoc-th is greater have higher accuracy.

These results indicate again that plans with replanning produce better accuracy. With a low BR(C), replanning is caused by the cognitive bound. With a medium BR(C) there is less need to replan because of cognitive limitations. Hence, where BR(C)=m, replanning occurs due to higher ecoc-th. The question that answers whether hypothesis-6 is confirmed or denied now depends on whether replanning due ECOC (with a higher threshold) has higher accuracy than bounded rationality (with a low BR(C)).

The results for Series 2 experiments have direct implications for hypothesis 6.

Hypothesis-6: Seemingly "irrational" behaviour can be emulated using a rational reasoner better when replanning based on ECOC threshold than just bounded rationality limits.

In Series 1 tests, best results were produced due to replanning caused by low BR(C) bounds. In Series 2 experiments, replanning was caused by either low BR(C) or the ecoc-th threshold where a medium BR(C) was used.

Accuracy for models where BR(C)=l with low ecoc-th threshold on average produce models with lower accuracy score. Where ecoc-th=0.1, accuracy is between 0.8 and 0.95, with the vast majority of models falling at or below 0.9. Accuracy for models where BR(C)=m with a high ecoc-th (greater than 0.2) on average produce models with a higher accuracy score of 1.0.

Hence, the hypothesis 6 is confirmed, models with ECOC produce more emulation than those with cognitive bounds only.

7. Conclusion

The results of the experiments indicate that some form of replanning is required to emulate the changing needs of clients. Several mean absolute errors (MAE) were used to evaluate proper cutoff thresholds for acceptable models. Acceptable models were those with a high true positive rate (TPR) and a low false positive rate (TPR).

The baseline configuration, which has no replanning, was observed to consistently produce among the worst TPR:FPR ratios of all configurations. Replanning was confirmed as important in the emulation of targeted populations. In BRAMA, replanning could be triggered in one of three ways. First, bounded rationality will cause an agent to defer goals because plans required to satisfy all goals are too large to fit within cognitive or time bounds. It was shown that BR(T) did not influence the results, however for Series 1 tests with a low BR(C) produced the better TPR:FPR ratios.

Second, the myopic and sophisticated strategies perform replanning at every time step using different conditions, as described in Chapter 4. For test configurations included here, the myopic strategy was tested with a medium BR(C) and BR(T). Bounds do not have a large impact on this strategy since utility is calculated one goal at a time and plans were found for each goal. Tests using the sophisticated strategy with a high BR(C) or BR(T) were not included in the results as they did not finish within the hour run-time limit. Instead, the sophisticated strategy was tested using low and medium BR(C) and BR(T). Any replanning was the result of a combination of the BR(C) and BR(T) bounds along with the sophisticated strategy. The resolute strategy with high BR(C) and BR(T) does not perform replanning. This was the baseline model's configuration. Tests included configurations with a low BR(C) and a resolute strategy, forcing replanning and producing better TPR:FPR ratios.

Third, replanning can be triggered and controlled by the ECOC thresholds ecoc-th and act-th for Series 2 tests. To isolate ECOC from other potential planning, Series 2 test configurations relied only on the resolute strategy during the planning phase, the ECOC utility function during the execution phase, the cognitive and time bounds, and ECOC thresholds greater than 0.0. High BR(C) and BR(T) limits were not included due to run-time limits.

Overall, the results indicate that a combination of the resolute strategy, a high ecoc-th value ($\geq$ 0.2), and either low or medium BR(C) value can be used to emulate how goals are replanned by CHF participants participating in social service program. This means that knowing the agent's strategy along with their emotional mood is less dependent on other factors, including BR(C), since both low and medium values for BR(C) produced acceptable results, with MAE cutoff of 2.0. If MAE cutoff of 1.0 is required, Series 2 results had best results with low BR(C) and resolute strategy. However, BR(C) may not be known by an observer. However, the strategy used by an agent and their emotional mood are observable. Identifying what ECOC stage an agent is in can be derived from interviews or observations. Emotions are an externally exhibited factor. Also, an agent's strategy can be observer from their behavior. Also, it is possible to tell if a subject is changing their priorities frequently (myopic), acting in a risk-neutral way (sophisticated) or sticking to an initial plan for as long as possible (resolute with replanning). Knowing their cognitive bound may be more difficult without closer examination in a controlled setting, something not always possible with the homeless population.

Appendix E.2: Test Data

This appendix provides the MAE values for tests and agents. There are 25 agents in total. Table 6 provides a mapping between the CHF participant's UID and Agent #. Table 7 provides the MAE value for all agents and tests.

Table 6. CHF Participant UID and Agent # Mapping.

UID	Agent #	UID	Agent #
adum02151980a400d300	1	mauf09301982m450a262	14
agkf06191984a200g200	2	mdef08181970m520d616	15
agum01011962a134g430	3	mpum02131969m624p400	16
dhwm12251957d130h630	4	mwlf04211955m645w426	17
drcm04221964d650r236	5	nhrf09191968n620h655	18
esim02261954e163s530	6	rlwm09111970r260l600	19
fsmf04071985f600s500	7	rrdm01031961r000r316	20
idrm08071958i150d600	8	slmf04011977s600l562	21
jfrm10251949j520f623	9	ssem04011962s500s152	22
jsmf03131967j500s542	10	szaf05101956s600z520	23
kcam02231967k530c160	11	whrm11061960w450h625	24
kkem02181966k622k622	12	wzem01051963w220z536	25
ldvf10221981l200d160	13		

Table 7. MAE values for all tests and agents, sorted by mean MAE.

									Agent #'s									
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	1	2	3	4	5	6	7	8	9	10
baseline	h	h	planutilswap	resolute	agent	exp	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		2.40
tn001	l	l	none	resolute	agent	exp	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn002	l	m	none	resolute	agent	exp	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn003	m	l	none	resolute	agent	exp	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn004	m	m	none	resolute	agent	exp	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn005	m	m	none	myopic	agent	exp	0	0	1.40	1.60	1.00	5.00	1.40	3.80	2.20	3.40	0.80	2.60
tn006	l	l	planutilswap	soph	agent	exp	0	0					1.40	3.60				
tn007	l	m	planutilswap	soph	agent	exp	0	0					1.40	3.60				
tn008	m	l	planutilswap	soph	agent	exp	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn009	m	m	planutilswap	soph	agent	exp	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn010	l	l	planutilswap	resolute	agent	exp	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn011	l	m	planutilswap	resolute	agent	exp	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn012	m	l	planutilswap	resolute	agent	exp	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn013	m	m	planutilswap	resolute	agent	exp	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn014	m	m	none	myopic	mh	exp	0	0	1.40	1.60	1.00	5.00	1.40	3.80	2.20	3.40	0.80	2.60
tn015	l	l	planutilswap	soph	mh	exp	0	0					1.40	3.60				
tn016	l	m	planutilswap	soph	mh	exp	0	0					1.40	3.60				
tn017	m	l	planutilswap	soph	mh	exp	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn018	m	m	planutilswap	soph	mh	exp	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn019	l	l	planutilswap	resolute	mh	exp	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn020	l	m	planutilswap	resolute	mh	exp	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn021	m	l	planutilswap	resolute	mh	exp	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn022	m	m	planutilswap	resolute	mh	exp	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn023	m	m	none	myopic	agent	ecoc	0	0	1.40	1.60	1.00	5.00	1.40	3.80	2.20	3.40	0.80	2.60

									Agent #'s									
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	1	2	3	4	5	6	7	8	9	10
tn024	l	l	planutilswap	soph	agent	ecoc	0	0					1.40	3.60				
tn025	l	m	planutilswap	soph	agent	ecoc	0	0					1.40	3.60				
tn026	m	l	planutilswap	soph	agent	ecoc	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn027	m	m	planutilswap	soph	agent	ecoc	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn028	l	l	planutilswap	resolute	agent	ecoc	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn029	l	m	planutilswap	resolute	agent	ecoc	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn030	m	l	planutilswap	resolute	agent	ecoc	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn031	m	m	planutilswap	resolute	agent	ecoc	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn032	m	m	none	myopic	mh	ecoc	0	0	1.40	1.60	1.00	5.00	1.40	3.80	2.20	3.40	0.80	2.60
tn033	l	l	planutilswap	soph	mh	ecoc	0	0					1.40	3.60				
tn034	l	m	planutilswap	soph	mh	ecoc	0	0					1.40	3.60				
tn035	m	l	planutilswap	soph	mh	ecoc	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn036	m	m	planutilswap	soph	mh	ecoc	0	0	1.20	1.60	1.40	5.00	1.40	3.60	1.20	3.40	0.80	
tn037	l	l	planutilswap	resolute	mh	ecoc	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn038	l	m	planutilswap	resolute	mh	ecoc	0	0	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn039	m	l	planutilswap	resolute	mh	ecoc	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn040	m	m	planutilswap	resolute	mh	ecoc	0	0	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn041	l	l	planutilswap	resolute	agent	ecoc	0.2	0.1	1.00	1.27	0.30	0.09	0.14	3.40	0.60	1.05	0.90	0.27
tn041a	l	l	planutilswap	resolute	agent	ecoc	0.1	0.1	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn042	l	m	planutilswap	resolute	agent	ecoc	0.2	0.1	1.00	1.27	0.63	0.09	0.14	3.40	0.53	1.05	0.90	0.27
tn042a	l	m	planutilswap	resolute	agent	ecoc	0.1	0.1	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn043	m	l	planutilswap	resolute	agent	ecoc	0.2	0.1	1.00	1.80	1.20	4.40	0.14	3.40	0.65	3.40	0.20	agerr
tn043a	m	l	planutilswap	resolute	agent	ecoc	0.1	0.1	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn044	m	m	planutilswap	resolute	agent	ecoc	0.2	0.1	1.00	1.80	1.20	4.40	0.14	3.40	0.65	3.40	0.20	agerr
tn044a	m	m	planutilswap	resolute	agent	ecoc	0.1	0.1	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60

									Agent #'s										
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	1	2	3	4	5	6	7	8	9	10
tn045	l	l	planutilswap	resolute	mh	ecoc	0.2	0.1	7.60	10.80	2.25	0.06	0.60	1.08	0.83	0.06	7.90	0.99
tn045a	l	l	planutilswap	resolute	mh	ecoc	0.1	0.1	5.50	7.40	2.33							
tn045b	l	l	planutilswap	resolute	mh	ecoc	0.05	0.1	1.00	0.60	3.98	0.67	1.60	3.40	0.35	1.05	0.20	0.27
tn046	l	m	planutilswap	resolute	mh	ecoc	0.2	0.1	7.60	10.80	1.65	0.06	0.60	1.08	0.83	0.06	5.80	0.99
tn046a	l	m	planutilswap	resolute	mh	ecoc	0.1	0.1	1.00	7.40	4.73							
tn046b	l	m	planutilswap	resolute	mh	ecoc	0.05	0.1	1.00	0.60	3.50	0.67	1.60	3.40	0.35	1.05	0.20	0.27
tn047	m	l	planutilswap	resolute	mh	ecoc	0.2	0.1	1.40	1.10	0.80	0.46	0.60	1.08	0.45	1.05	0.70	2.54
tn047a	m	l	planutilswap	resolute	mh	ecoc	0.1	0.1	1.00	0.60	0.70							
tn047b	m	l	planutilswap	resolute	mh	ecoc	0.05	0.1	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		agerr
tn048	m	m	planutilswap	resolute	mh	ecoc	0.2	0.1	1.40	1.10	0.80	0.46	0.60	1.08	0.45	1.05	0.70	agerr
tn048a	m	m	planutilswap	resolute	mh	ecoc	0.1	0.1	1.00	0.60	1.20							
tn048b	m	m	planutilswap	resolute	mh	ecoc	0.05	0.1	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.27
tn049	l	l	planutilswap	resolute	agent	ecoc	0.4	0.1	12.10	11.40	agerr	0.04	0.60	1.08	1.48	0.06	3.80	1.98
tn050	l	m	planutilswap	resolute	agent	ecoc	0.4	0.1	13.10	11.70	2.25	0.04	0.60	1.08	1.55	0.06	9.40	2.30
tn051	m	l	planutilswap	resolute	agent	ecoc	0.4	0.1	1.40	1.20	0.73	0.46	0.60	1.08	0.53	1.13	0.70	4.06
tn052	m	m	planutilswap	resolute	agent	ecoc	0.4	0.1	1.40	1.20	0.83	0.46	0.60	1.08	0.45	1.05	0.70	agerr
tn053	l	l	planutilswap	resolute	mh	ecoc	0.4	0.1	12.40	11.80	2.20	0.04	0.60	1.08	1.48	0.06	9.20	1.98
tn054	l	m	planutilswap	resolute	mh	ecoc	0.4	0.1	13.10	11.80	1.50	0.04	0.60	1.08	1.55	0.06	4.50	2.07
tn055	m	l	planutilswap	resolute	mh	ecoc	0.4	0.1	1.70	1.10	0.80	0.46	0.60	1.08	0.53	1.13	3.20	3.40
tn056	m	m	planutilswap	resolute	mh	ecoc	0.4	0.1	1.00	1.10	0.80	0.46	0.60	1.08	0.45	1.05	0.70	3.40
tn057	l	l	planutilswap	resolute	agent	ecoc	0.6	0.1	12.60	11.50	2.03	0.04	0.60	1.08	1.48	0.06	3.80	1.99
tn058	l	m	planutilswap	resolute	agent	ecoc	0.6	0.1	13.60	11.80	2.10	0.04	0.60	1.08	1.55	0.06	9.40	2.27

									Agent #'s									
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	1	2	3	4	5	6	7	8	9	10
tn059	m	l	planutilswap	resolute	agent	ecoc	0.6	0.1	1.00	1.20	0.80	0.46	0.60	1.08	0.53	1.13	0.70	4.07
tn060	m	m	planutilswap	resolute	agent	ecoc	0.6	0.1	1.00	1.20	0.80	0.46	0.60	1.08	0.45	1.05	0.70	agerr
tn061	l	l	planutilswap	resolute	mh	ecoc	0.6	0.1	12.20	11.80	2.20	0.04	0.60	1.08	1.48	0.06	9.20	1.98
tn062	l	m	planutilswap	resolute	mh	ecoc	0.6	0.1	12.90	11.80	1.50	0.04	0.60	1.08	1.55	0.06	4.50	2.07
tn063	m	l	planutilswap	resolute	mh	ecoc	0.6	0.1	1.70	1.10	0.80	0.46	0.60	1.08	0.53	1.13	3.20	3.40
tn064	m	m	planutilswap	resolute	mh	ecoc	0.6	0.1	1.00	1.10	0.80	0.46	0.60	1.08	0.45	1.05	0.70	3.40
tn065	l	l	planutilswap	resolute	agent	ecoc	0.2	0.3	2.10	6.10								
tn066	l	m	planutilswap	resolute	agent	ecoc	0.2	0.3	2.10	1.90								
tn067	m	l	planutilswap	resolute	agent	ecoc	0.2	0.3	2.10									
tn068	m	m	planutilswap	resolute	agent	ecoc	0.2	0.3	2.10									
tn069	l	l	planutilswap	resolute	mh	ecoc	0.2	0.3	4.20	9.90	agerr	0.05	0.15	0.29	3.90	0.05	10.90	1.02
tn069a	l	l	planutilswap	resolute	mh	ecoc	0.1	0.3	0.80	3.40	agerr	0.07	1.60	3.40	0.35	0.19	4.30	1.28
tn069aa	l	l	planutilswap	resolute	agent	ecoc	0.1	0.3	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn070	l	m	planutilswap	resolute	mh	ecoc	0.2	0.3	4.80	9.90	agerr	0.04	0.15	0.29	3.90	0.13	2.60	1.02
tn070a	l	m	planutilswap	resolute	mh	ecoc	0.1	0.3	1.00	3.40	agerr	0.18	1.60	3.40	0.35	agerr	4.30	0.42
tn070aa	l	m	planutilswap	resolute	agent	ecoc	0.1	0.3	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn071	m	l	planutilswap	resolute	mh	ecoc	0.2	0.3	1.60	1.50	0.70	1.50	0.15	0.29	0.43	1.05	1.40	1.26
tn071a	m	l	planutilswap	resolute	mh	ecoc	0.1	0.3	1.00	0.60	0.70	4.40	1.60	3.40	0.43	3.40		1.74
tn071aa	m	l	planutilswap	resolute	agent	ecoc	0.1	0.3	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn072	m	m	planutilswap	resolute	mh	ecoc	0.2	0.3	1.80	1.50	0.70	1.50	0.15	0.29	0.43	1.05	1.40	1.26
tn072a	m	m	planutilswap	resolute	mh	ecoc	0.1	0.3	1.00	0.60	1.20	4.40	1.60	3.40	0.43	3.40		1.74
tn072aa	m	m	planutilswap	resolute	agent	ecoc	0.1	0.3	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn073	l	l	planutilswap	resolute	agent	ecoc	0.4	0.3	8.10	10.00	agerr	0.04	0.15	0.29	2.40	0.05	agerr	0.97
tn074	l	m	planutilswap	resolute	agent	ecoc	0.4	0.3	agerr	11.30	agerr	0.06	0.15	0.29	2.78	agerr	agerr	agerr

									Agent #'s									
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	1	2	3	4	5	6	7	8	9	10
tn075	m	l	planutilswap	resolute	agent	ecoc	0.4	0.3	1.80	1.10	0.70	1.50	0.15	0.29	0.45	1.05	1.40	1.24
tn076	m	m	planutilswap	resolute	agent	ecoc	0.4	0.3	1.80	1.50	0.70	1.50	0.15	0.29	0.43	1.05	1.40	agerr
tn077	l	l	planutilswap	resolute	mh	ecoc	0.4	0.3	5.70	10.00	agerr	0.04	0.13	0.17	2.38	0.05	10.00	0.97
tn078	l	m	planutilswap	resolute	mh	ecoc	0.4	0.3	5.70	10.00	agerr	0.05	0.13	0.17	2.75	0.14	12.80	0.97
tn079	m	l	planutilswap	resolute	mh	ecoc	0.4	0.3	1.80	1.50	0.70	1.50	0.13	0.17	0.45	1.05	1.40	1.24
tn080	m	m	planutilswap	resolute	mh	ecoc	0.4	0.3	1.80	1.50	0.70	1.50	0.13	0.17	0.43	1.05	1.40	1.24
tn081	l	l	planutilswap	resolute	agent	ecoc	0.6	0.3	8.30	9.60	agerr	0.04	0.13	0.29	2.55	0.05	12.40	1.30
tn082	l	m	planutilswap	resolute	agent	ecoc	0.6	0.3	9.80	12.20	agerr	0.06	0.13	0.29	2.55	0.16	12.40	1.47
tn083	m	l	planutilswap	resolute	agent	ecoc	0.6	0.3	1.80	1.20	0.70	1.50	0.13	0.29	0.43	1.05	1.40	1.84
tn084	m	m	planutilswap	resolute	agent	ecoc	0.6	0.3	1.80	1.50	0.70	1.50	0.13	0.29	0.43	1.05	1.40	2.01
tn085	l	l	planutilswap	resolute	mh	ecoc	0.6	0.3	8.30	9.60	agerr	0.04	0.13	0.17	2.58	0.05	9.40	1.30
tn086	l	m	planutilswap	resolute	mh	ecoc	0.6	0.3	8.30	9.60	agerr	0.05	0.13	0.17	2.58	0.14	12.40	1.30
tn087	m	l	planutilswap	resolute	mh	ecoc	0.6	0.3	1.80	1.50	0.70	1.50	0.13	0.17	0.43	1.05	1.40	1.84
tn088	m	m	planutilswap	resolute	mh	ecoc	0.6	0.3	1.80	1.50	0.70	1.50	0.13	0.17	0.43	1.05	1.40	1.84
tn089	l	l	planutilswap	resolute	agent	ecoc	0.1	0.5	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn090	l	m	planutilswap	resolute	agent	ecoc	0.1	0.5	1.00	0.60	0.30	1.40	1.60	3.40	0.35	1.05	0.20	0.27
tn091	m	l	planutilswap	resolute	agent	ecoc	0.1	0.5	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn092	m	m	planutilswap	resolute	agent	ecoc	0.1	0.5	1.00	0.60	1.20	4.40	1.60	3.40	1.00	3.40		0.60
tn093	l	l	planutilswap	resolute	mh	ecoc	0.1	0.5	3.50	3.40	1.63	0.14	1.60	3.40	0.35	0.19	4.30	0.63
tn094	l	m	planutilswap	resolute	mh	ecoc	0.1	0.5	1.00	3.40	2.68	0.17	1.60	3.40	0.35	0.09	4.30	1.89
tn095	m	l	planutilswap	resolute	mh	ecoc	0.1	0.5	1.00	0.60	0.45	4.40	1.60	3.40	0.43	3.40		1.36
tn096	m	m	planutilswap	resolute	mh	ecoc	0.1	0.5	1.00	0.60	1.20	4.40	1.60	3.40	0.43	3.40		1.36
tn097	l	l	planutilswap	resolute	mh	ecoc	0.2	0.5	4.20	9.80	1.35	0.06	0.60	1.08	3.95	0.05	10.90	1.02
tn098	l	m	planutilswap	resolute	mh	ecoc	0.2	0.5	4.80	9.80	1.05	0.04	0.60	1.08	3.95	0.13	7.50	1.02

									Agent #'s									
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	1	2	3	4	5	6	7	8	9	10
tn099	m	l	planutilswap	resolute	mh	ecoc	0.2	0.5	1.60	1.50	0.45	1.50	0.60	1.08	0.43	1.05	1.40	1.26
tn100	m	m	planutilswap	resolute	agent	ecoc	0.4	0.5	1.80	1.50	0.45	1.50	0.60	1.08	0.43	1.05	1.40	agerr
tn100	m	m	planutilswap	resolute	mh	ecoc	0.2	0.5	1.80	1.50	0.45	1.50	0.60	1.08	0.43	1.05	1.40	1.26
tn101	l	l	planutilswap	resolute	agent	ecoc	0.4	0.5	5.80	9.90	1.30	0.04	0.60	1.08	2.40	0.05	agerr	1.00
tn102	l	m	planutilswap	resolute	agent	ecoc	0.4	0.5	agerr	11.40	1.30	agerr	0.60	1.08	2.80	agerr	agerr	agerr
tn103	m	l	planutilswap	resolute	agent	ecoc	0.4	0.5	1.80	1.10	0.45	1.50	0.60	1.08	0.45	1.18	1.40	1.28
tn105	l	l	planutilswap	resolute	mh	ecoc	0.4	0.5	5.80	9.90	1.38	0.04	0.60	1.08	2.40	0.05	10.00	1.00
tn106	l	m	planutilswap	resolute	mh	ecoc	0.4	0.5	5.80	10.00	1.43	0.05	0.60	1.08	2.78	agerr	12.80	1.00
tn107	m	l	planutilswap	resolute	mh	ecoc	0.4	0.5	1.80	1.50	0.35	1.50	0.60	1.08	0.45	1.05	1.40	1.28
tn108	m	m	planutilswap	resolute	mh	ecoc	0.4	0.5	1.80	1.50	0.45	1.50	0.60	1.08	0.43	1.05	1.40	1.28
tn109	l	l	planutilswap	resolute	agent	ecoc	0.6	0.5	8.40	9.20	1.35	0.04	0.60	1.08	3.78	0.05	12.40	1.33
tn110	l	m	planutilswap	resolute	agent	ecoc	0.6	0.5	9.80	agerr	1.35	0.07	0.60	1.08	3.80	agerr	12.40	1.47
tn111	m	l	planutilswap	resolute	agent	ecoc	0.6	0.5	1.80	1.20	0.45	1.50	0.60	1.08	0.43	1.05	1.40	1.88
tn112	m	m	planutilswap	resolute	agent	ecoc	0.6	0.5	1.80	1.50	0.45	1.50	0.60	1.08	0.43	1.05	1.40	2.01
tn113	l	l	planutilswap	resolute	mh	ecoc	0.6	0.5	8.60	9.20	1.38	0.04	0.60	1.08	agerr	0.05	9.40	1.33
tn114	l	m	planutilswap	resolute	mh	ecoc	0.6	0.5	8.60	9.20	1.43	0.05	0.60	1.08	agerr	agerr	12.40	1.33
tn115	m	l	planutilswap	resolute	mh	ecoc	0.6	0.5	1.80	1.50	0.35	1.50	0.60	1.08	0.43	1.05	1.40	1.88
tn116	m	m	planutilswap	resolute	mh	ecoc	0.6	0.5	1.80	1.50	0.45	1.50	0.60	1.08	0.43	1.05	1.40	1.88

									Agent #'s										
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	11	12	13	14	15	16	17	18	19	20	21
baseline	h	h	planutilswap	resolute	agent	exp	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn001	l	l	none	resolute	agent	exp	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn002	l	m	none	resolute	agent	exp	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn003	m	l	none	resolute	agent	exp	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn004	m	m	none	resolute	agent	exp	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn005	m	m	none	myopic	agent	exp	0	0	4.00	1.80	2.20	1.20	1.60	1.60	1.00	1.80	3.40	2.40	1.40
tn006	l	l	planutilswap	soph	agent	exp	0	0							1.20				1.40
tn007	l	m	planutilswap	soph	agent	exp	0	0							1.20				1.40
tn008	m	l	planutilswap	soph	agent	exp	0	0	6.00	2.20	2.40	1.20	1.80	1.60	1.20	2.00	3.40	2.80	1.40
tn009	m	m	planutilswap	soph	agent	exp	0	0	6.00	2.20	2.40	1.20	1.80	1.60	1.20	2.00	3.40	2.80	1.40
tn010	l	l	planutilswap	resolute	agent	exp	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn011	l	m	planutilswap	resolute	agent	exp	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn012	m	l	planutilswap	resolute	agent	exp	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn013	m	m	planutilswap	resolute	agent	exp	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn014	m	m	none	myopic	mh	exp	0	0	4.00	1.80	2.20	1.20	1.60	1.60	1.00	1.80	3.40	2.40	1.40
tn015	l	l	planutilswap	soph	mh	exp	0	0							1.20				1.40
tn016	l	m	planutilswap	soph	mh	exp	0	0							1.20				1.40
tn017	m	l	planutilswap	soph	mh	exp	0	0	4.00	1.80	2.40	1.20	1.60	1.20	1.20	1.60	3.40	2.40	1.40
tn018	m	m	planutilswap	soph	mh	exp	0	0	4.00	1.80	2.40	1.20	1.60	1.20	1.20	1.60	3.40	2.40	1.40
tn019	l	l	planutilswap	resolute	mh	exp	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn020	l	m	planutilswap	resolute	mh	exp	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn021	m	l	planutilswap	resolute	mh	exp	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn022	m	m	planutilswap	resolute	mh	exp	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn023	m	m	none	myopic	agent	ecoc	0	0	4.00	1.80	2.20	1.20	1.60	1.60	1.00	1.80	3.40	2.40	1.40
tn024	l	l	planutilswap	soph	agent	ecoc	0	0							1.20				1.40
tn025	l	m	planutilswap	soph	agent	ecoc	0	0							1.20				1.40

									Agent #'s										
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	11	12	13	14	15	16	17	18	19	20	21
tn026	m	l	planutilswap	soph	agent	ecoc	0	0	6.00	2.20	2.40	1.20	1.80	1.60	1.20	2.00	3.40	2.80	1.40
tn027	m	m	planutilswap	soph	agent	ecoc	0	0	6.00	2.20	2.40	1.20	1.80	1.60	1.20	2.00	3.40	2.80	1.40
tn028	l	l	planutilswap	resolute	agent	ecoc	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn029	l	m	planutilswap	resolute	agent	ecoc	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn030	m	l	planutilswap	resolute	agent	ecoc	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn031	m	m	planutilswap	resolute	agent	ecoc	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn032	m	m	none	myopic	mh	ecoc	0	0	4.00	1.80	2.20	1.20	1.60	1.60	1.00	1.80	3.40	2.40	1.40
tn033	l	l	planutilswap	soph	mh	ecoc	0	0							1.20				1.40
tn034	l	m	planutilswap	soph	mh	ecoc	0	0							1.20				1.40
tn035	m	l	planutilswap	soph	mh	ecoc	0	0	4.00	1.80	2.40	1.20	1.60	1.20	1.20	1.60	3.40	2.40	1.40
tn036	m	m	planutilswap	soph	mh	ecoc	0	0	4.00	1.80	2.40	1.20	1.60	1.20	1.20	1.60	3.40	2.40	1.40
tn037	l	l	planutilswap	resolute	mh	ecoc	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn038	l	m	planutilswap	resolute	mh	ecoc	0	0	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn039	m	l	planutilswap	resolute	mh	ecoc	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn040	m	m	planutilswap	resolute	mh	ecoc	0	0	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn041	l	l	planutilswap	resolute	agent	ecoc	0.2	0.1	0.25	1.03	0.55	1.30	0.60	0.55	1.20	0.53	0.33	0.60	1.40
tn041a	l	l	planutilswap	resolute	agent	ecoc	0.1	0.1	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn042	l	m	planutilswap	resolute	agent	ecoc	0.2	0.1	0.25	1.03	0.55	1.10	0.60	0.55	1.20	0.36	0.33	0.60	1.40
tn042a	l	m	planutilswap	resolute	agent	ecoc	0.1	0.1	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn043	m	l	planutilswap	resolute	agent	ecoc	0.2	0.1	4.00	1.80	2.20	1.00	1.60	1.00	1.20	1.40	0.53	2.20	1.40
tn043a	m	l	planutilswap	resolute	agent	ecoc	0.1	0.1	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn044	m	m	planutilswap	resolute	agent	ecoc	0.2	0.1	4.00	1.80	2.20	1.00	1.60	1.00	1.20	1.40	0.53	2.20	1.40
tn044a	m	m	planutilswap	resolute	agent	ecoc	0.1	0.1	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn045	l	l	planutilswap	resolute	mh	ecoc	0.2	0.1	0.08	0.32	0.15	8.70	1.83	0.98	0.21	0.19	0.25	0.33	0.38
tn045a	l	l	planutilswap	resolute	mh	ecoc	0.1	0.1											
tn045b	l	l	planutilswap	resolute	mh	ecoc	0.05	0.1	0.17	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.44	0.95	1.40

									Agent #'s										
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	11	12	13	14	15	16	17	18	19	20	21
tn046	l	m	planutilswap	resolute	mh	ecoc	0.2	0.1	0.07	0.32	0.15	7.70	1.83	0.98	0.21	0.19	0.18	0.33	0.38
tn046a	l	m	planutilswap	resolute	mh	ecoc	0.1	0.1											
tn046b	l	m	planutilswap	resolute	mh	ecoc	0.05	0.1	0.17	0.55	0.55	0.80	4.13	0.55	1.20	0.55	0.44	0.95	1.40
tn047	m	l	planutilswap	resolute	mh	ecoc	0.2	0.1	1.15	0.29	0.65	1.30	0.65	0.29	0.21	0.58	0.62	0.54	0.38
tn047a	m	l	planutilswap	resolute	mh	ecoc	0.1	0.1											
tn047b	m	l	planutilswap	resolute	mh	ecoc	0.05	0.1	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn048	m	m	planutilswap	resolute	mh	ecoc	0.2	0.1	1.15	0.29	0.65	1.30	0.65	0.29	0.21	0.58	0.62	0.54	0.38
tn048a	m	m	planutilswap	resolute	mh	ecoc	0.1	0.1											
tn048b	m	m	planutilswap	resolute	mh	ecoc	0.05	0.1	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn049	l	l	planutilswap	resolute	agent	ecoc	0.4	0.1	0.06	0.31	0.15	8.20	1.80	1.10	0.40	0.15	0.20	0.66	0.38
tn050	l	m	planutilswap	resolute	agent	ecoc	0.4	0.1	0.07	0.31	0.15	7.60	1.88	1.10	0.40	0.16	0.27	0.71	0.38
tn051	m	l	planutilswap	resolute	agent	ecoc	0.4	0.1	1.23	0.29	0.65	1.30	0.73	0.29	0.40	0.50	0.59	0.62	0.38
tn052	m	m	planutilswap	resolute	agent	ecoc	0.4	0.1	1.15	0.29	0.65	1.30	0.65	0.29	0.40	0.58	0.62	0.62	0.38
tn053	l	l	planutilswap	resolute	mh	ecoc	0.4	0.1	0.07	0.30	0.15	8.10	1.80	1.10	0.40	0.15	0.20	0.65	0.38
tn054	l	m	planutilswap	resolute	mh	ecoc	0.4	0.1	0.07	0.30	0.15	7.50	1.88	1.10	0.40	0.16	0.27	0.68	0.38
tn055	m	l	planutilswap	resolute	mh	ecoc	0.4	0.1	1.23	0.29	0.65	1.30	0.73	0.29	0.40	0.50	0.59	0.63	0.38
tn056	m	m	planutilswap	resolute	mh	ecoc	0.4	0.1	1.15	0.29	0.65	1.30	0.65	0.29	0.40	0.58	0.62	0.62	0.38
tn057	l	l	planutilswap	resolute	agent	ecoc	0.6	0.1	0.06	0.31	0.15	8.10	1.80	1.10	0.40	0.15	0.20	0.66	0.38
tn058	l	m	planutilswap	resolute	agent	ecoc	0.6	0.1	0.07	0.31	0.15	7.50	1.88	1.10	0.40	0.16	0.29	0.72	0.38
tn059	m	l	planutilswap	resolute	agent	ecoc	0.6	0.1	1.23	0.29	0.65	1.30	0.73	0.29	0.40	0.50	0.59	0.62	0.38
tn060	m	m	planutilswap	resolute	agent	ecoc	0.6	0.1	1.15	0.29	0.65	1.30	0.65	0.29	0.40	0.58	0.62	0.62	0.38
tn061	l	l	planutilswap	resolute	mh	ecoc	0.6	0.1	0.07	0.30	0.15	8.10	1.80	1.10	0.40	0.15	0.20	0.68	0.38
tn062	l	m	planutilswap	resolute	mh	ecoc	0.6	0.1	0.07	0.30	0.15	7.50	1.88	1.10	0.40	0.16	0.29	0.68	0.38
tn063	m	l	planutilswap	resolute	mh	ecoc	0.6	0.1	1.23	0.29	0.65	1.30	0.73	0.29	0.40	0.50	0.59	0.63	0.38
tn064	m	m	planutilswap	resolute	mh	ecoc	0.6	0.1	1.15	0.29	0.65	1.30	0.65	0.29	0.40	0.58	0.62	0.62	0.38
tn065	l	l	planutilswap	resolute	agent	ecoc	0.2	0.3											

									Agent #'s											
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	11	12	13	14	15	16	17	18	19	20	21
tn066	l	m	planutilswap	resolute	agent	ecoc	0.2	0.3											
tn067	m	l	planutilswap	resolute	agent	ecoc	0.2	0.3											
tn068	m	m	planutilswap	resolute	agent	ecoc	0.2	0.3											
tn069	l	l	planutilswap	resolute	mh	ecoc	0.2	0.3	0.07	1.06	0.51	agerr	1.73	agerr	0.45	0.79	0.13	0.20	0.31
tn069a	l	l	planutilswap	resolute	mh	ecoc	0.1	0.3	0.15	0.67	0.55	0.80	1.35	agerr	1.20	0.23	0.45	0.31	1.40
tn069aa	l	l	planutilswap	resolute	agent	ecoc	0.1	0.3	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn070	l	m	planutilswap	resolute	mh	ecoc	0.2	0.3	0.07	1.06	0.49	9.30	1.73	agerr	0.45	agerr	0.14	0.23	0.31
tn070a	l	m	planutilswap	resolute	mh	ecoc	0.1	0.3	0.15	0.54	0.55	0.80	1.50	3.04	1.20	0.23	0.16	0.95	1.40
tn070aa	l	m	planutilswap	resolute	agent	ecoc	0.1	0.3	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn071	m	l	planutilswap	resolute	mh	ecoc	0.2	0.3	1.15	0.38	0.65	1.20	0.65	0.65	0.45	0.58	1.05	0.73	0.31
tn071a	m	l	planutilswap	resolute	mh	ecoc	0.1	0.3	4.00	1.80	1.15	0.80	1.60	1.00	1.20	0.18	3.20	2.20	1.40
tn071aa	m	l	planutilswap	resolute	agent	ecoc	0.1	0.3	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn072	m	m	planutilswap	resolute	mh	ecoc	0.2	0.3	1.15	0.38	0.65	1.20	0.65	0.65	0.45	0.58	1.05	0.78	0.31
tn072a	m	m	planutilswap	resolute	mh	ecoc	0.1	0.3	4.00	1.80	2.20	0.80	1.60	1.00	1.20	0.18	3.20	2.20	1.40
tn072aa	m	m	planutilswap	resolute	agent	ecoc	0.1	0.3	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn073	l	l	planutilswap	resolute	agent	ecoc	0.4	0.3	0.05	1.21	agerr	9.60	3.78	agerr	0.17	0.47	0.12	0.24	0.31
tn074	l	m	planutilswap	resolute	agent	ecoc	0.4	0.3	0.05	1.21	0.63	11.00	3.78	1.96	0.17	0.51	0.13	0.50	0.31
tn075	m	l	planutilswap	resolute	agent	ecoc	0.4	0.3	1.15	0.38	0.65	1.60	0.65	0.65	0.17	0.58	1.05	0.78	0.31
tn076	m	m	planutilswap	resolute	agent	ecoc	0.4	0.3	1.15	0.38	0.65	1.20	0.65	0.65	0.17	0.58	1.05	0.78	0.31
tn077	l	l	planutilswap	resolute	mh	ecoc	0.4	0.3	0.06	agerr	0.53	agerr	2.80	agerr	0.17	0.36	0.18	0.27	0.31
tn078	l	m	planutilswap	resolute	mh	ecoc	0.4	0.3	0.06	agerr	0.56	8.30	2.80	agerr	0.17	0.49	0.13	0.27	0.31
tn079	m	l	planutilswap	resolute	mh	ecoc	0.4	0.3	1.15	0.38	0.65	1.60	0.65	0.65	0.17	0.58	1.05	0.78	0.31
tn080	m	m	planutilswap	resolute	mh	ecoc	0.4	0.3	1.15	0.38	0.65	1.20	0.65	0.65	0.17	0.58	1.05	0.78	0.31
tn081	l	l	planutilswap	resolute	agent	ecoc	0.6	0.3	0.05	1.04	0.53	9.20	3.55	agerr	0.17	0.36	0.12	0.24	0.31
tn082	l	m	planutilswap	resolute	agent	ecoc	0.6	0.3	0.05	1.04	0.56	11.90	3.55	1.96	0.17	0.53	0.13	0.51	0.31
tn083	m	l	planutilswap	resolute	agent	ecoc	0.6	0.3	1.15	0.38	0.65	0.90	0.65	0.65	0.17	0.58	1.05	0.78	0.31

									Agent #'s										
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	11	12	13	14	15	16	17	18	19	20	21
tn084	m	m	planutilswap	resolute	agent	ecoc	0.6	0.3	1.15	0.38	0.65	1.20	0.65	0.65	0.17	0.58	1.05	0.78	0.31
tn085	l	l	planutilswap	resolute	mh	ecoc	0.6	0.3	0.06	0.86	0.53	13.70	3.55	agerr	0.17	0.36	0.12	0.24	0.31
tn086	l	m	planutilswap	resolute	mh	ecoc	0.6	0.3	0.06	0.86	0.56	9.00	3.55	agerr	0.17	0.49	0.13	0.24	0.31
tn087	m	l	planutilswap	resolute	mh	ecoc	0.6	0.3	1.15	0.38	0.65	1.20	0.65	0.65	0.17	0.58	1.05	0.78	0.31
tn088	m	m	planutilswap	resolute	mh	ecoc	0.6	0.3	1.15	0.38	0.65	1.20	0.65	0.65	0.17	0.58	1.05	0.78	0.31
tn089	l	l	planutilswap	resolute	agent	ecoc	0.1	0.5	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn090	l	m	planutilswap	resolute	agent	ecoc	0.1	0.5	1.00	0.55	0.55	0.80	0.60	0.55	1.20	0.55	0.90	0.95	1.40
tn091	m	l	planutilswap	resolute	agent	ecoc	0.1	0.5	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn092	m	m	planutilswap	resolute	agent	ecoc	0.1	0.5	4.00	1.80	2.20	0.80	1.60	1.00	1.20	1.40	3.20	2.20	1.40
tn093	l	l	planutilswap	resolute	mh	ecoc	0.1	0.5	0.15	0.67	0.55	0.80	2.25	agerr	1.20	0.23	0.42	0.31	1.40
tn094	l	m	planutilswap	resolute	mh	ecoc	0.1	0.5	0.15	0.54	0.55	0.80	1.50	3.01	1.20	0.23	0.16	0.95	1.40
tn095	m	l	planutilswap	resolute	mh	ecoc	0.1	0.5	4.00	1.80	0.23	0.80	1.60	1.00	1.20	0.18	3.20	2.20	1.40
tn096	m	m	planutilswap	resolute	mh	ecoc	0.1	0.5	4.00	1.80	2.20	0.80	1.60	1.00	1.20	0.18	3.20	2.20	1.40
tn097	l	l	planutilswap	resolute	mh	ecoc	0.2	0.5	0.07	0.26	0.51	12.60	2.43	agerr	0.45	0.75	0.13	0.20	0.38
tn098	l	m	planutilswap	resolute	mh	ecoc	0.2	0.5	0.07	0.26	0.54	9.40	2.43	agerr	0.45	0.61	0.14	0.23	0.38
tn099	m	l	planutilswap	resolute	mh	ecoc	0.2	0.5	1.15	0.63	0.65	1.20	0.65	0.65	0.45	0.58	0.90	0.73	0.38
tn100	m	m	planutilswap	resolute	agent	ecoc	0.4	0.5	1.15	0.63	0.65	1.20	0.65	0.65	0.40	0.58	1.05	0.78	0.38
tn100	m	m	planutilswap	resolute	mh	ecoc	0.2	0.5	1.15	0.63	0.65	1.20	0.65	0.65	0.45	0.58	1.05	0.78	0.38
tn101	l	l	planutilswap	resolute	agent	ecoc	0.4	0.5	0.06	0.26	agerr	9.60	4.15	agerr	0.40	0.40	0.21	0.36	0.38
tn102	l	m	planutilswap	resolute	agent	ecoc	0.4	0.5	0.06	0.24	0.62	11.10	4.15	agerr	0.40	0.43	0.21	agerr	0.38
tn103	m	l	planutilswap	resolute	agent	ecoc	0.4	0.5	1.15	0.58	0.65	1.60	0.65	0.65	0.40	0.70	1.05	0.78	0.38
tn105	l	l	planutilswap	resolute	mh	ecoc	0.4	0.5	0.06	0.26	0.56	agerr	4.15	agerr	0.40	0.36	0.21	0.36	0.38
tn106	l	m	planutilswap	resolute	mh	ecoc	0.4	0.5	0.06	0.26	0.56	8.40	4.15	agerr	0.40	0.53	0.21	0.36	0.38
tn107	m	l	planutilswap	resolute	mh	ecoc	0.4	0.5	1.15	0.63	0.65	1.60	0.65	0.65	0.40	0.58	1.05	0.78	0.38
tn108	m	m	planutilswap	resolute	mh	ecoc	0.4	0.5	1.15	0.63	0.65	1.20	0.65	0.65	0.40	0.58	1.05	0.78	0.38
tn109	l	l	planutilswap	resolute	agent	ecoc	0.6	0.5	0.06	0.26	0.58	8.90	agerr	agerr	0.40	0.36	0.21	0.40	0.38

									Agent #'s											
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	11	12	13	14	15	16	17	18	19	20	21
tn110	l	m	planutilswap	resolute	agent	ecoc	0.6	0.5	0.06	0.24	0.56	agerr	agerr	agerr	0.40	0.48	0.21	0.54	0.38
tn111	m	l	planutilswap	resolute	agent	ecoc	0.6	0.5	1.15	0.58	0.65	0.90	0.65	0.65	0.40	0.58	1.05	0.78	0.38
tn112	m	m	planutilswap	resolute	agent	ecoc	0.6	0.5	1.15	0.63	0.65	1.20	0.65	0.65	0.40	0.58	1.05	0.78	0.38
tn113	l	l	planutilswap	resolute	mh	ecoc	0.6	0.5	0.06	0.26	0.58	13.80	agerr	agerr	0.40	0.36	0.21	0.40	0.38
tn114	l	m	planutilswap	resolute	mh	ecoc	0.6	0.5	0.06	0.26	0.56	9.20	agerr	agerr	0.40	0.53	0.21	0.40	0.38
tn115	m	l	planutilswap	resolute	mh	ecoc	0.6	0.5	1.15	0.63	0.65	0.90	0.65	0.65	0.40	0.58	1.05	0.78	0.38
tn116	m	m	planutilswap	resolute	mh	ecoc	0.6	0.5	1.15	0.63	0.65	1.20	0.65	0.65	0.40	0.58	1.05	0.78	0.38

									Agent #'s				
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	21	22	23	24	25
baseline	h	h	planutilswap	resolute	agent	exp	0	0	1.40	1.80	0.40	5.00	1.00
tn001	l	l	none	resolute	agent	exp	0	0	1.40	0.65	0.30	1.25	1.00
tn002	l	m	none	resolute	agent	exp	0	0	1.40	0.65	0.30	1.25	1.00
tn003	m	l	none	resolute	agent	exp	0	0	1.40	1.80	0.40	5.00	1.00
tn004	m	m	none	resolute	agent	exp	0	0	1.40	1.80	0.40	5.00	1.00
tn005	m	m	none	myopic	agent	exp	0	0	1.40	1.40	0.60	5.00	1.20
tn006	l	l	planutilswap	soph	agent	exp	0	0	1.40				1.60
tn007	l	m	planutilswap	soph	agent	exp	0	0	1.40				1.60
tn008	m	l	planutilswap	soph	agent	exp	0	0	1.40	1.60	1.20	5.00	1.60
tn009	m	m	planutilswap	soph	agent	exp	0	0	1.40	1.60	1.20	5.00	1.60
tn010	l	l	planutilswap	resolute	agent	exp	0	0	1.40	0.65	0.30	1.25	1.00
tn011	l	m	planutilswap	resolute	agent	exp	0	0	1.40	0.65	0.30	1.25	1.00
tn012	m	l	planutilswap	resolute	agent	exp	0	0	1.40	1.80	0.40	5.00	1.00
tn013	m	m	planutilswap	resolute	agent	exp	0	0	1.40	1.80	0.40	5.00	1.00
tn014	m	m	none	myopic	mh	exp	0	0	1.40	1.40	0.60	5.00	1.20
tn015	l	l	planutilswap	soph	mh	exp	0	0	1.40				1.60
tn016	l	m	planutilswap	soph	mh	exp	0	0	1.40				1.60
tn017	m	l	planutilswap	soph	mh	exp	0	0	1.40	1.40	0.60	5.00	1.60
tn018	m	m	planutilswap	soph	mh	exp	0	0	1.40	1.40	0.60	5.00	1.60
tn019	l	l	planutilswap	resolute	mh	exp	0	0	1.40	0.65	0.30	1.25	1.00
tn020	l	m	planutilswap	resolute	mh	exp	0	0	1.40	0.65	0.30	1.25	1.00
tn021	m	l	planutilswap	resolute	mh	exp	0	0	1.40	1.80	0.40	5.00	1.00
tn022	m	m	planutilswap	resolute	mh	exp	0	0	1.40	1.80	0.40	5.00	1.00
tn023	m	m	none	myopic	agent	ecoc	0	0	1.40	1.40	0.60	5.00	1.20
tn024	l	l	planutilswap	soph	agent	ecoc	0	0	1.40				1.60

									Agent #'s				
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	21	22	23	24	25
tn025	l	m	planutilswap	soph	agent	ecoc	0	0	1.40				1.60
tn026	m	l	planutilswap	soph	agent	ecoc	0	0	1.40	1.60	1.20	5.00	1.60
tn027	m	m	planutilswap	soph	agent	ecoc	0	0	1.40	1.60	1.20	5.00	1.60
tn028	l	l	planutilswap	resolute	agent	ecoc	0	0	1.40	0.65	0.30	1.25	1.00
tn029	l	m	planutilswap	resolute	agent	ecoc	0	0	1.40	0.65	0.30	1.25	1.00
tn030	m	l	planutilswap	resolute	agent	ecoc	0	0	1.40	1.80	0.40	5.00	1.00
tn031	m	m	planutilswap	resolute	agent	ecoc	0	0	1.40	1.80	0.40	5.00	1.00
tn032	m	m	none	myopic	mh	ecoc	0	0	1.40	1.40	0.60	5.00	1.20
tn033	l	l	planutilswap	soph	mh	ecoc	0	0	1.40				1.60
tn034	l	m	planutilswap	soph	mh	ecoc	0	0	1.40				1.60
tn035	m	l	planutilswap	soph	mh	ecoc	0	0	1.40	1.40	0.60	5.00	1.60
tn036	m	m	planutilswap	soph	mh	ecoc	0	0	1.40	1.40	0.60	5.00	1.60
tn037	l	l	planutilswap	resolute	mh	ecoc	0	0	1.40	0.65	0.30	1.25	1.00
tn038	l	m	planutilswap	resolute	mh	ecoc	0	0	1.40	0.65	0.30	1.25	1.00
tn039	m	l	planutilswap	resolute	mh	ecoc	0	0	1.40	1.80	0.40	5.00	1.00
tn040	m	m	planutilswap	resolute	mh	ecoc	0	0	1.40	1.80	0.40	5.00	1.00
tn041	l	l	planutilswap	resolute	agent	ecoc	0.2	0.1	1.40	0.93	0.30	1.25	1.00
tn041a	l	l	planutilswap	resolute	agent	ecoc	0.1	0.1	1.40	0.65	0.30	1.25	1.00
tn042	l	m	planutilswap	resolute	agent	ecoc	0.2	0.1	1.40	0.65	0.30	1.25	1.00
tn042a	l	m	planutilswap	resolute	agent	ecoc	0.1	0.1	1.40	0.65	0.30	1.25	1.00
tn043	m	l	planutilswap	resolute	agent	ecoc	0.2	0.1	1.40	1.80	0.40	5.00	1.00
tn043a	m	l	planutilswap	resolute	agent	ecoc	0.1	0.1	1.40	1.80	0.40	5.00	1.00
tn044	m	m	planutilswap	resolute	agent	ecoc	0.2	0.1	1.40	1.80	0.40	5.00	1.00
tn044a	m	m	planutilswap	resolute	agent	ecoc	0.1	0.1	1.40	1.80	0.40	5.00	1.00
tn045	l	l	planutilswap	resolute	mh	ecoc	0.2	0.1	0.38	0.60	2.40	0.05	1.50
tn045a	l	l	planutilswap	resolute	mh	ecoc	0.1	0.1					

									Agent #'s				
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	21	22	23	24	25
tn045b	l	l	planutilswap	resolute	mh	ecoc	0.05	0.1	1.40	agerr	0.30	1.25	1.00
tn046	l	m	planutilswap	resolute	mh	ecoc	0.2	0.1	0.38	0.50	2.40	0.05	1.50
tn046a	l	m	planutilswap	resolute	mh	ecoc	0.1	0.1					
tn046b	l	m	planutilswap	resolute	mh	ecoc	0.05	0.1	1.40	agerr	0.30	1.25	1.00
tn047	m	l	planutilswap	resolute	mh	ecoc	0.2	0.1	0.38	0.26	0.80	1.35	1.50
tn047a	m	l	planutilswap	resolute	mh	ecoc	0.1	0.1					
tn047b	m	l	planutilswap	resolute	mh	ecoc	0.05	0.1	1.40	1.80	0.40	5.00	1.00
tn048	m	m	planutilswap	resolute	mh	ecoc	0.2	0.1	0.38	0.26	0.70	1.35	1.50
tn048a	m	m	planutilswap	resolute	mh	ecoc	0.1	0.1					
tn048b	m	m	planutilswap	resolute	mh	ecoc	0.05	0.1	1.40	1.80	0.40	5.00	1.00
tn049	l	l	planutilswap	resolute	agent	ecoc	0.4	0.1	0.38	0.51	4.58	0.05	1.50
tn050	l	m	planutilswap	resolute	agent	ecoc	0.4	0.1	0.38	0.51	4.90	0.05	1.50
tn051	m	l	planutilswap	resolute	agent	ecoc	0.4	0.1	0.38	0.26	0.80	1.43	1.50
tn052	m	m	planutilswap	resolute	agent	ecoc	0.4	0.1	0.38	0.26	0.80	1.35	1.50
tn053	l	l	planutilswap	resolute	mh	ecoc	0.4	0.1	0.38	0.54	4.58	0.05	1.50
tn054	l	m	planutilswap	resolute	mh	ecoc	0.4	0.1	0.38	0.54	4.78	0.05	1.50
tn055	m	l	planutilswap	resolute	mh	ecoc	0.4	0.1	0.38	0.26	1.13	1.43	1.50
tn056	m	m	planutilswap	resolute	mh	ecoc	0.4	0.1	0.38	0.26	0.80	1.35	1.50
tn057	l	l	planutilswap	resolute	agent	ecoc	0.6	0.1	0.38	0.51	4.60	0.05	1.50
tn058	l	m	planutilswap	resolute	agent	ecoc	0.6	0.1	0.38	0.51	4.93	0.05	1.50
tn059	m	l	planutilswap	resolute	agent	ecoc	0.6	0.1	0.38	0.26	0.80	1.43	1.50
tn060	m	m	planutilswap	resolute	agent	ecoc	0.6	0.1	0.38	0.26	0.80	1.35	1.50
tn061	l	l	planutilswap	resolute	mh	ecoc	0.6	0.1	0.38	0.54	4.58	0.05	1.50
tn062	l	m	planutilswap	resolute	mh	ecoc	0.6	0.1	0.38	0.54	4.78	0.05	1.50
tn063	m	l	planutilswap	resolute	mh	ecoc	0.6	0.1	0.38	0.26	1.13	1.43	1.50
tn064	m	m	planutilswap	resolute	mh	ecoc	0.6	0.1	0.38	0.26	0.80	1.35	1.50

									Agent #'s				
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	21	22	23	24	25
tn065	l	l	planutilswap	resolute	agent	ecoc	0.2	0.3					
tn066	l	m	planutilswap	resolute	agent	ecoc	0.2	0.3					
tn067	m	l	planutilswap	resolute	agent	ecoc	0.2	0.3					
tn068	m	m	planutilswap	resolute	agent	ecoc	0.2	0.3					
tn069	l	l	planutilswap	resolute	mh	ecoc	0.2	0.3	0.31	1.97	1.48	0.05	1.50
tn069a	l	l	planutilswap	resolute	mh	ecoc	0.1	0.3	1.40	1.98	1.60	1.25	1.00
tn069aa	l	l	planutilswap	resolute	agent	ecoc	0.1	0.3	1.40	0.65	0.30	1.25	1.00
tn070	l	m	planutilswap	resolute	mh	ecoc	0.2	0.3	0.31	1.97	1.55	0.05	1.50
tn070a	l	m	planutilswap	resolute	mh	ecoc	0.1	0.3	1.40	1.98	1.35	1.25	1.00
tn070aa	l	m	planutilswap	resolute	agent	ecoc	0.1	0.3	1.40	0.65	0.30	1.25	1.00
tn071	m	l	planutilswap	resolute	mh	ecoc	0.2	0.3	0.31	0.34	0.50	1.35	1.50
tn071a	m	l	planutilswap	resolute	mh	ecoc	0.1	0.3	1.40	1.80	0.40	5.00	1.00
tn071aa	m	l	planutilswap	resolute	agent	ecoc	0.1	0.3	1.40	1.80	0.40	5.00	1.00
tn072	m	m	planutilswap	resolute	mh	ecoc	0.2	0.3	0.31	0.34	0.48	1.35	1.50
tn072a	m	m	planutilswap	resolute	mh	ecoc	0.1	0.3	1.40	1.80	0.40	5.00	1.00
tn072aa	m	m	planutilswap	resolute	agent	ecoc	0.1	0.3	1.40	1.80	0.40	5.00	1.00
tn073	l	l	planutilswap	resolute	agent	ecoc	0.4	0.3	0.31	agerr	1.90	0.04	1.50
tn074	l	m	planutilswap	resolute	agent	ecoc	0.4	0.3	0.31	agerr	agerr	0.04	1.50
tn075	m	l	planutilswap	resolute	agent	ecoc	0.4	0.3	0.31	0.34	0.48	1.35	1.50
tn076	m	m	planutilswap	resolute	agent	ecoc	0.4	0.3	0.31	0.34	0.48	1.35	1.50
tn077	l	l	planutilswap	resolute	mh	ecoc	0.4	0.3	0.31	agerr	1.90	0.04	1.50
tn078	l	m	planutilswap	resolute	mh	ecoc	0.4	0.3	0.31	agerr	1.90	0.04	1.50
tn079	m	l	planutilswap	resolute	mh	ecoc	0.4	0.3	0.31	0.34	0.48	1.35	1.50
tn080	m	m	planutilswap	resolute	mh	ecoc	0.4	0.3	0.31	0.34	0.48	1.35	1.50
tn081	l	l	planutilswap	resolute	agent	ecoc	0.6	0.3	0.31	1.88	2.45	0.04	1.50
tn082	l	m	planutilswap	resolute	agent	ecoc	0.6	0.3	0.31	1.88	3.58	0.04	1.50

									Agent #'s				
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	21	22	23	24	25
tn083	m	l	planutilswap	resolute	agent	ecoc	0.6	0.3	0.31	0.34	0.48	1.35	1.50
tn084	m	m	planutilswap	resolute	agent	ecoc	0.6	0.3	0.31	0.34	0.48	1.35	1.50
tn085	l	l	planutilswap	resolute	mh	ecoc	0.6	0.3	0.31	1.58	1.90	0.04	1.50
tn086	l	m	planutilswap	resolute	mh	ecoc	0.6	0.3	0.31	1.58	1.90	0.04	1.50
tn087	m	l	planutilswap	resolute	mh	ecoc	0.6	0.3	0.31	0.34	0.48	1.35	1.50
tn088	m	m	planutilswap	resolute	mh	ecoc	0.6	0.3	0.31	0.34	0.48	1.35	1.50
tn089	l	l	planutilswap	resolute	agent	ecoc	0.1	0.5	1.40	0.65	0.30	1.25	1.00
tn090	l	m	planutilswap	resolute	agent	ecoc	0.1	0.5	1.40	0.65	0.30	1.25	1.00
tn091	m	l	planutilswap	resolute	agent	ecoc	0.1	0.5	1.40	1.80	0.40	5.00	1.00
tn092	m	m	planutilswap	resolute	agent	ecoc	0.1	0.5	1.40	1.80	0.40	5.00	1.00
tn093	l	l	planutilswap	resolute	mh	ecoc	0.1	0.5	1.40	0.50	1.60	1.25	1.00
tn094	l	m	planutilswap	resolute	mh	ecoc	0.1	0.5	1.40	0.50	1.35	1.25	1.00
tn095	m	l	planutilswap	resolute	mh	ecoc	0.1	0.5	1.40	1.80	0.40	5.00	1.00
tn096	m	m	planutilswap	resolute	mh	ecoc	0.1	0.5	1.40	1.80	0.40	5.00	1.00
tn097	l	l	planutilswap	resolute	mh	ecoc	0.2	0.5	0.38	0.43	1.48	0.05	1.50
tn098	l	m	planutilswap	resolute	mh	ecoc	0.2	0.5	0.38	0.46	1.55	0.05	1.50
tn099	m	l	planutilswap	resolute	mh	ecoc	0.2	0.5	0.38	0.55	0.50	1.35	1.50
tn100	m	m	planutilswap	resolute	agent	ecoc	0.4	0.5	0.38	0.55	0.48	1.35	1.50
tn100	m	m	planutilswap	resolute	mh	ecoc	0.2	0.5	0.38	0.55	0.48	1.35	1.50
tn101	l	l	planutilswap	resolute	agent	ecoc	0.4	0.5	0.38	0.43	1.93	0.04	1.50
tn102	l	m	planutilswap	resolute	agent	ecoc	0.4	0.5	0.38	0.49	agerr	0.04	1.50
tn103	m	l	planutilswap	resolute	agent	ecoc	0.4	0.5	0.38	0.65	0.48	1.35	1.50
tn105	l	l	planutilswap	resolute	mh	ecoc	0.4	0.5	0.38	0.43	2.73	0.04	1.50
tn106	l	m	planutilswap	resolute	mh	ecoc	0.4	0.5	0.38	0.43	2.73	0.04	1.50
tn107	m	l	planutilswap	resolute	mh	ecoc	0.4	0.5	0.38	0.55	0.48	1.35	1.50
tn108	m	m	planutilswap	resolute	mh	ecoc	0.4	0.5	0.38	0.55	0.48	1.35	1.50

									Agent #'s				
testn	brc	brt	planutil	strategy	pref	executil	ecocth	actionth	21	22	23	24	25
tn109	l	l	planutilswap	resolute	agent	ecoc	0.6	0.5	0.38	0.43	2.48	0.04	1.50
tn110	l	m	planutilswap	resolute	agent	ecoc	0.6	0.5	0.38	0.49	3.58	0.04	1.50
tn111	m	l	planutilswap	resolute	agent	ecoc	0.6	0.5	0.38	0.65	0.48	1.35	1.50
tn112	m	m	planutilswap	resolute	agent	ecoc	0.6	0.5	0.38	0.55	0.48	1.35	1.50
tn113	l	l	planutilswap	resolute	mh	ecoc	0.6	0.5	0.38	0.43	2.65	0.04	1.50
tn114	l	m	planutilswap	resolute	mh	ecoc	0.6	0.5	0.38	0.43	2.65	0.04	1.50
tn115	m	l	planutilswap	resolute	mh	ecoc	0.6	0.5	0.38	0.55	0.48	1.35	1.50
tn116	m	m	planutilswap	resolute	mh	ecoc	0.6	0.5	0.38	0.55	0.48	1.35	1.50