Sri Lanka Society of Transport and Logistics

Journal of South Asian Logistics and Transport
Volume 4 Issue 1 March 2024
JSALT 4.1.6: pp. 119-144
DOI: https://doi.org/10.4038/jsalt.v4i1.90

AN AGENT-BASED CROWD DYNAMICS SIMULATION THAT CONSIDERS IDLING AND TIME-AND-DISTANCE-CONSCIOUS OPTIMISING BEHAVIOUR

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ABSTRACT

This agent-based simulation study investigates pedestrian dynamics with a focus on the impacts of behaviour idling on pedestrian flows. It also examines the influence of psychological, social, and environmental factors on pedestrian flows. Our research categorises pedestrian behaviour into three types: time-sensitive (Type A), mobility-constrained (Type B), and 'wandering' type (Type C), defined as pedestrians moving without a specific destination, which includes tourists, shoppers, and leisure walkers. We demonstrate how behaviour heterogeneity influences flow and movement patterns through simulations in unidirectional, bi-directional, and multi-directional pedestrian facilities. We find that Type C pedestrians significantly slow down Type A pedestrians, leading to a speed reduction of up to 30% in high-density tourist scenarios, and cause prolonged stationary periods for Type B pedestrians, particularly in less crowded settings where Type C's tendency to idle is more pronounced. Our results show a linear relationship between density and speed reduction, with tourist behaviour notably exacerbating congestion in high-density environments. Key insights highlight the critical role of wandering (Type C) behaviours in affecting pedestrian flow, emphasising the necessity for urban planning and infrastructure design to accommodate this variability. Future research aims to apply these findings to real-world contexts, further refining urban design strategies to accommodate the full spectrum of pedestrian behaviours.

Keywords: *Agent-based, heterogeneous, pedestrian dynamic, pedestrian behaviour, microsimulation, crowds*

1. INTRODUCTION

Research on pedestrian and crowd dynamics has many applications including the design of safer, more efficient pedestrian facilities in urban areas and evaluation of evacuation strategies [1], [2], [3], [4]. The definition of a 'crowd' can differ greatly among academic disciplines; a crowd is described as autonomous agents in computer science, particles that interact with each other in physics, and collective actors in sociology [5]. There is extensive literature on crowd behaviour simulation and numerous methods of simulating such behaviour have been proposed. A critical assessment of pedestrian behaviour models can be found in Papadimitriou et al.'s [6] study.

Crowd behaviour has been simulated through two general approaches: macroscopic and microscopic modelling. Macroscopic models are often based on traffic flow theory, queuing theory, continuum theory, or fluid and gas dynamics [1], [6], [7], [8]. In such modelling a crowd is treated as a continuous homogeneous density (numerous individuals in a large physique) changing over time and space. Microscopic frameworks model crowds as an aggregation of an individual evolution in time and space permitting interactions among each other [6], [8], [9], [10], [11] Cellular automata (CA) are some of the oldest approaches in microscopic modelling in which each individual follows a simple set of rules while advancing through a discrete grid cell space [12], [13], [14]. Social force models [15] queuing models [16], and Markovian models [17] are examples of these microscopic simulation models in addition to CA.

In recent years, advancements in microscopic techniques - notably multi-agent simulation models - have pushed toward achieving greater realism in the study of crowd dynamics [18], [19], [20], [21]. These models have yielded significant insights into density and speed profiles among pedestrians. However, they often do not capture the cognitive and social dimensions of pedestrian behaviour elements crucial for generating more realistic simulations of crowd dynamics. This oversight underscores a need for more focus on individuals' social objectives, identities, and psychological behaviours, which are fundamental to understanding pedestrian movements within crowds [18]. While models incorporating the social sciences and psychology aspects of pedestrian behaviour exist, these models rely on qualitative descriptions and do not attempt to replicate these behaviours algorithmically [22].

The literature reveals a need for deeper exploration of pedestrians' complex and varied behaviours, which are crucial in affecting urban pedestrian dynamics. Existing models fail to accommodate the full spectrum of pedestrian behaviours observed in real-world settings, from bustling shopping malls to busy airport terminals, where pedestrians not only navigate physical obstacles but also interact with their environment and each other in complex ways. To address this need and to begin incorporating multi-objective psychological criteria into traditional models, we propose a three-tiered pedestrian simulation model that leverages a cellular automata grid structure to encompass the heterogeneity among pedestrians.

The CA model is an essential tool for this purpose, providing the flexibility to adjust cell size and customise logic to accurately simulate pedestrian movements and behaviours [12], [23], [24]. The CA model can replicate the complex dynamics seen in pedestrian crowds through simple, localised rules, effectively capturing the emergent outcomes of individual decisions on overall flow patterns[12]. The adaptability and detailed granularity of the CA model and its ability to include heterogeneous behaviours through tailored rules offer a nuanced understanding essential for designing safer, more efficient, and inclusive urban spaces.

By relying on the strengths of the cellular automata model, our study seeks to fill the identified research gap, offering new insights into pedestrian dynamics. Furthermore, this paper examines the impact of pedestrians' behavioural differences on fundamental movement parameters and how these agent types navigate crowded spaces. This approach not only deepens our comprehension of pedestrian behaviour but also equips urban planners and policymakers with a refined tool for developing vibrant, functional public areas that meet the community’s diverse needs.

2. PREVIOUS WORK: WHY AND HOW WE MOVE

Psychological and social factors have a significant influence on pedestrian decision-making. Goffman [25] and Rymill and Dodgson [26] argue that unlike in the case of cars, a pedestrian’s primary goal is not just to get from one point to another, but instead includes intermittent activities such as idling, shopping, stopping, and surveying their surroundings, or chatting. Pedestrians do tend to behave in a somewhat orderly fashion by not pushing and shoving each other out of the way or colliding with each other [26], supporting the effectiveness of CA and grid-based modelling on pedestrians. Previous work has shown that the average speed of a pedestrian varies based on certain factors such as age, gender, walking alongside others, trip purpose, layout of walking facilities, mood, and environmental conditions such as rain and cold. Pedestrians tend to walk faster when they walk alongside others, if the pedestrian happens to be an adult male, when it is raining and colder or those who place higher emphasis on saving time [26], [27], [28], [29]. In terms of crossing behaviour, pedestrians tend to take risks and violate traffic rules when others do so, or when the pedestrians are younger [30], [31], [32].

Pedestrians who walked to work daily were observed to be always "in a hurry" when walking [33]. Time conscious walking behaviour is expected in many individuals running to catch a bus or train or to be on time for a significant activity. Hill [33] also adds that some fraction of pedestrians refuses to give up their right of way until the last moment. This group of individuals always tries to minimize the deviation from their original desired path by displaying distance-conscious walking behaviour. Avoiding collisions, taking detours, overtaking, slowing down, and step-and-slide (swapping spaces without collision) are noted as the most important and most apparent aspects of behaviour among pedestrians [26]. Goffman [25] explains that pedestrians on a collision course may make eye contact to express their intentions to ensure that all parties understand each other. Step-and-slide is observed to be the most prominent collision avoidance approach for pedestrians who are more reluctant to deviate from their current path, which narrowly prevents a collision by stepping aside or just moving around one another [26]. Usually, detours are formed when a pedestrian cannot match the walking speed of pedestrians in front of them or to avoid collision with the opposing pedestrian traffic. Formation of lanes occurs when pedestrians slow down and walk behind a cluster of individuals walking at roughly the same speed in the same direction. Overtaking happens when pedestrians wish to walk faster than the speed of the cluster (or the lane) in front of them, and those who overtake will do so in a manner to ensure that such manoeuvres will not cause a collision with oncoming pedestrians [26].

A model that realistically describes pedestrian movements must accommodate all these apparent psychological and social behaviours among pedestrians. In addition to the dynamics described above, pedestrians who spend time idling, surveying, walking while looking at their phones, shopping, or chatting could create a less homogeneous walking environment for those who wish to move quickly and may act as slow-moving or stationary obstacles for others to avoid.

This paper proposes a simulation model incorporating aspects of this heterogeneity among pedestrians, including time and distance-conscious walking behaviour. The heterogeneity of pedestrian behaviour is crucial as it can affect overall flow and movement patterns. It is vital to have all these heterogeneities and apparent behavioural aspects in a unified pedestrian model, where individuals may not use the walking facilities only to reach one point to another and may not act homogeneously. For example, walking in a shopping mall might be crowded with window shopping pedestrians, salespeople, and stalls. In an airport, pedestrians might try to minimize their walking distance because they are carrying heavy luggage, stop to look for signage to find the way to a terminal, or run towards a gate before it closes. Walking facilities might be blocked due to construction, street-side vendors, trees, or a side bench. The design of such walking facilities cannot only consider space for walkers but needs to consider heterogeneous aspects of pedestrians, such as individuals with mobility issues and surface obstacles, to prevent building extremely uncomfortable, crowded, and unsafe walking environments. If not, pedestrians might take unsafe detours using spaces where they are not supposed to be, such as stepping onto highways, or confront unpleasant congested situations that force pedestrians to push one another and invoke equity issues in accessibility.

In addition to the heterogeneity, this pedestrian simulation captures idling and coherent behaviour, such as collision avoidance, detouring, overtaking, slowing down, and step-and-slide or stopping, in a unified model. We have also introduced obstacles that pedestrians must navigate around and a type of pedestrian who acts as non-stationary obstacles for others to avoid, such as individuals who look at their phones and are not mindful of their surroundings, which simulate more realistic walking situations.

Cooper and Elithorn [34] and Hill [33] argued that “Pedestrian route selection is, in fact, a big-as-life game played on a city-wide game board” and “winning” means reaching the desired destination successfully. In this proposed model, in addition to the fact it captures the heterogeneity and rational behaviour among pedestrians, we adopted the sociological conceptual viewpoint of a board game in determining the route of such pedestrians.

The following section introduces the model and “updating rules” of three distinct pedestrian behaviours used in the model. In Section 4, a simulation is run with these agents under various conditions, and the results of the simulations are discussed in Section 5. Section 6 discusses policy implications and provides a summary of findings. A concluding statement and discussion of future work are outlined in Section 7.

3. MODEL

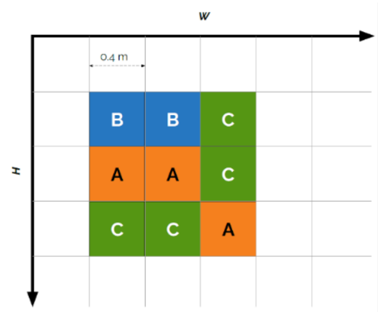
The proposed agent-based model is defined using a two-dimensional cellular grid of width W and height H (see Figure 1a), commonly seen in pedestrian models using cellular automata [14]. Each cell can either be empty, occupied by an obstacle, or occupied by precisely one pedestrian. Though the transition of cell states does not follow traditional cellular automata rules, the dimensions of the grid follow the studies of Blue and Adler [14] and Burstedde et al. [24], and the size of a cell corresponds to approximately $0.4 \times 0.4\ \mathrm{m}^2$; the typical space occupied by a pedestrian in a dense crowd.

Based on their movement objectives, a three-tiered classification of agents (pedestrians) has been introduced in this proposed model: Type A (Movers), Type B

(Distance minimisers), and Type C (Tourists). Using a grid similar to the cellular automata model makes the simulation more straightforward and comprehensible. The taxonomy of such agent types is discussed comprehensively in the following section 3.2. Before introducing the individual characteristics of each agent, we outline how movement is executed on the grid.

3.1. Movement on the Grid

Movement is controlled by a centralised grid of width W and height H which allows individuals to take one action per "turn", or simulation step (Figure 1a). At most, agents can move only one cell per iteration, which gives the agents a maximum possible velocity of one cell per time step (1.33m/s or 4.79km/h)[1].Type A agents act first, followed by Type B and Type C agents. Each agent type goes in a random order within their class for each round of moves. Based on their desired movement behaviour described in Section 3.2 each agent will either move one space in any orthogonal or diagonal direction from their current spot (Figure 1b) or remain stationary. After all agents on the board have moved, turn order is re-shuffled among agent types and a new round is played.



(a)

$C_{(-1,-1)}$	$C_{(-1,0)}$	$C_{(-1,1)}$
$C_{(0,-1)}$	$C_{(0,0)}$	$C_{(0,1)}$
$C_{(1,-1)}$	$C_{(1,0)}$	$C_{(1,1)}$

(b)

Figure 1: Grid and choices definition for behaviour model. (a) Grid definition with potential agent placement. (b) Matrix C_{ij} of choices available to agent at (0,0)

The grid is implemented computationally through the Python package NetworkX [35]. Each cell is represented by a node, connected to adjacent nodes with a bi-directional edge. Shortest paths from an agent's current position to their destination is calculated using the well-known A* algorithm with a Euclidean distance heuristic [36]. The A* algorithm was chosen over alternatives such as Dijkstra or Bellman-Ford due to its speed and ability to vary choices when multiple shortest-path alternatives exist.

[1] Alternate speeds can be achieved by resizing the size definition of a single cell or adjusting the time step.

Each simulation run requires a target density ρ, and the simulation is broken into two phases: warm-up and steady state. In the warm-up phase, agents are placed in designated “spawn points” at the edge of the scenario grid as the simulation runs[2], gradually adding more agents until the target density for a given scenario is reached or exceeded. Once agents start leaving the grid and the density falls below ρ, agents are spawned to maintain the target density, and the simulation enters the steady-state phase. After a specified number of steady-state steps, the simulation ends, and data for the steady-state portion is obtained.

The choice of what type of agent is generated is based on a target ratio of A:B:C agent types. During the simulation, the target ratio is compared with the actual mixture of agents, and the type of agent spawned is randomly chosen using probabilities that correspond with the need for a given agent type. For example, if the number of agents needed to reach a target mixture of A:B:C is 10, 5, and 0 respectively, the simulation is twice as likely to generate a Type A agent compared with a Type B agent. The generated agent is placed in an unoccupied cell in the designated spawning areas. This process ensures that a target mixture of agents is held steady throughout the scenario, and allows us to study differences in speed, and idle time under different mixing of pedestrians. Finally, generated agents are given a target destination at a random cell on the edge of the grid in a designated spawn area that is not their own. For example, in a four-way grid scenario, an agent spawned on the bottom of the grid is given a destination either on the left, the right, or the top of the grid.

3.2. Classification of Heterogeneous Agents and Their Updating Rules

In this simulation model, a three-tiered classification of pedestrians has been proposed according to their collective behaviour to demonstrate evident heterogeneous conduct among pedestrians as they walk, as discussed in Section 1. The classification of agents and their collective objectives are illustrated in Table 1.

Table 1: Classification of pedestrians by objectives

Classification	Objective
Type A (Movers)	Minimise access time to their destination. Stopping averse; will always try to keep moving.
Type B (Distance minimisers)	Minimise access distance to their destination. Will give way to others to achieve their objective.
Type C (Tourists)	Move haphazardly and in a stochastic manner. No distance or time-related objectives.

[2] These areas are marked with pink boxes in figures that show the grid configuration for a given scenario.

3.2.1. Type A: Movers

Type A agents are labelled as "movers", as they represent pedestrians who place a high value on continuous movement and speed in their travel. They will move into any unoccupied cell that brings them closer or keeps them as close to their destination as they were previously. This may cause them to take a longer path than is necessary.

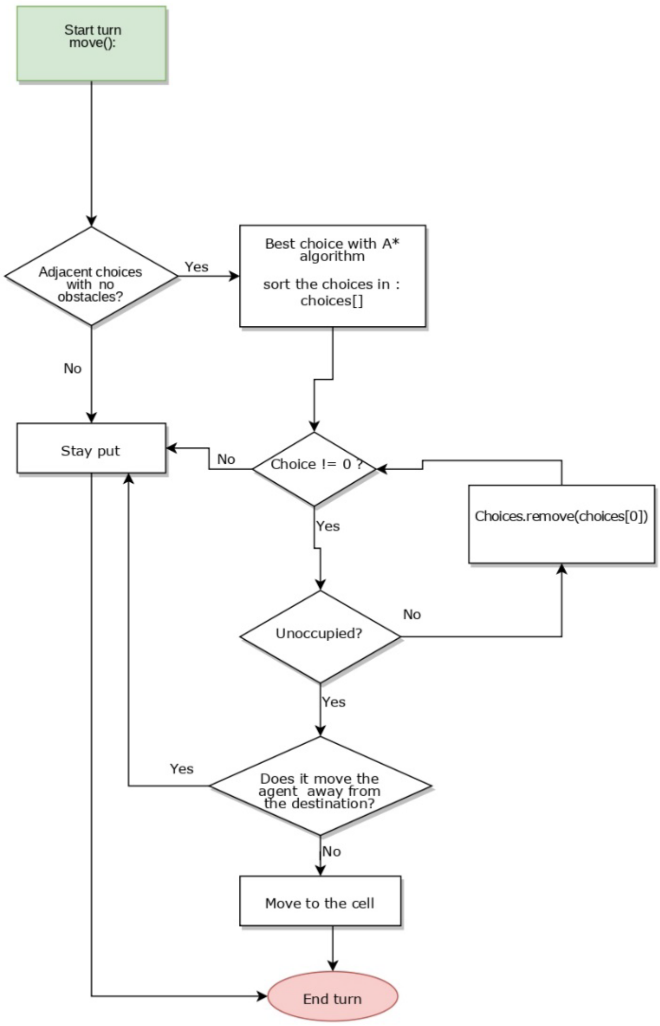


Figure 2: Decision flow chart of Type A agents

However, they may reach their destination faster. Under free flow conditions (when pedestrian volumes are low and obstacles are absent), movers will always take the shortest path by A* algorithm, which allows them to accomplish their motive of minimising the time by minimising the distance simultaneously. Their least appealing choice is to stay put (stopping) and will do so only when all other alternatives result in taking them further from the desired destination.

Individual updating rules are diagrammed in Figure 2 summarised as follows:

1. Check the adjacent cell that moves the agent in the direction of the shortest path towards the desired destination.
2. If that cell is free, move there and end turn.
3. If that cell is occupied (by agent or obstacle), continue to check the next best cells that does not move the agent away from its destination. Move there and end turn.
4. If no cells are available that do not move the agent away from its destination, stay put and end turn.

3.2.2. Type B: Distance Minimizers

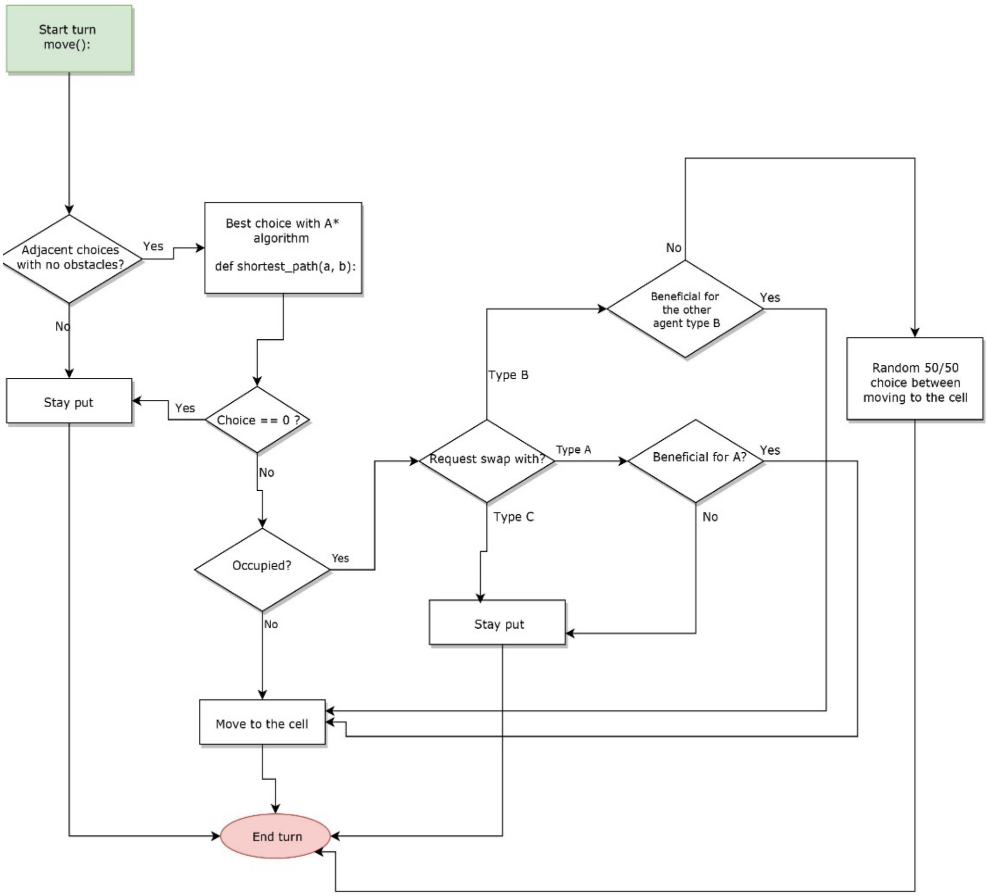


Figure 3: Decision flow chart of Type B agents.

Type B agents are named "distance minimisers" as they represent pedestrians who value shorter-distance travel, perhaps encumbered by age or other mobility issues. They always move towards their desired destination along the shortest path possible using the A* algorithm. If the shortest path is not available, they will stay still until an anticipated path frees for them to continue. Since the shortest path is always applied under this category, no different strategy is used under free-flow conditions.

However, Type B agents have the option to “swap”, which allows them to request a switch with another agent’s space. A request for a swap is handled by the model framework which passes the demand on to the anticipated agent. The receiver of such a request will evaluate the benefit of complying and will accommodate the swap under a particular set of conditions. Individual updating rules are diagrammed in Figure 3 and summarised as follows:

1. Check the adjacent cell that moves the agent in the direction of the shortest path towards the desired destination.
2. If that cell is free, move there and end turn.
3. If that cell is occupied by an agent:
   - Type B: If the swap is beneficial for the occupying agent and the agent has not already moved this turn, perform a swap and end turn.
   - Type C: If the occupying agent has not moved this turn, perform a swap and end turn.

3.2.3. Type C: Tourists

Type C agents are named “tourists” as these agents do not have any agenda of minimising time or distance in the initial stage of entering the study area. They survey their surrounding cells and randomly choose an unoccupied cell to move to, giving priority to all other agent types. This type illustrates the most erratic behaviour compared to the other two types, where each agent randomly changes their moving strategies throughout all turns (time steps) inside the grid and acts as stationary or moving obstacles for other agent types. Individual updating rules are diagrammed in Figure 4 and summarised as follows:

1. Randomly choose to either stay put, move randomly, or move towards their eventual destination (1/3 probability for each):
   - If “stay put” is chosen, end turn without moving.
   - If “move randomly” is chosen, choose an adjacent cell at random, move to it if unoccupied, and end turn.
   - If “move towards destination” is chosen, choose the cell that moves that agent in the direction of the shortest past towards the desired destination. Move there if not occupied, and end turn.

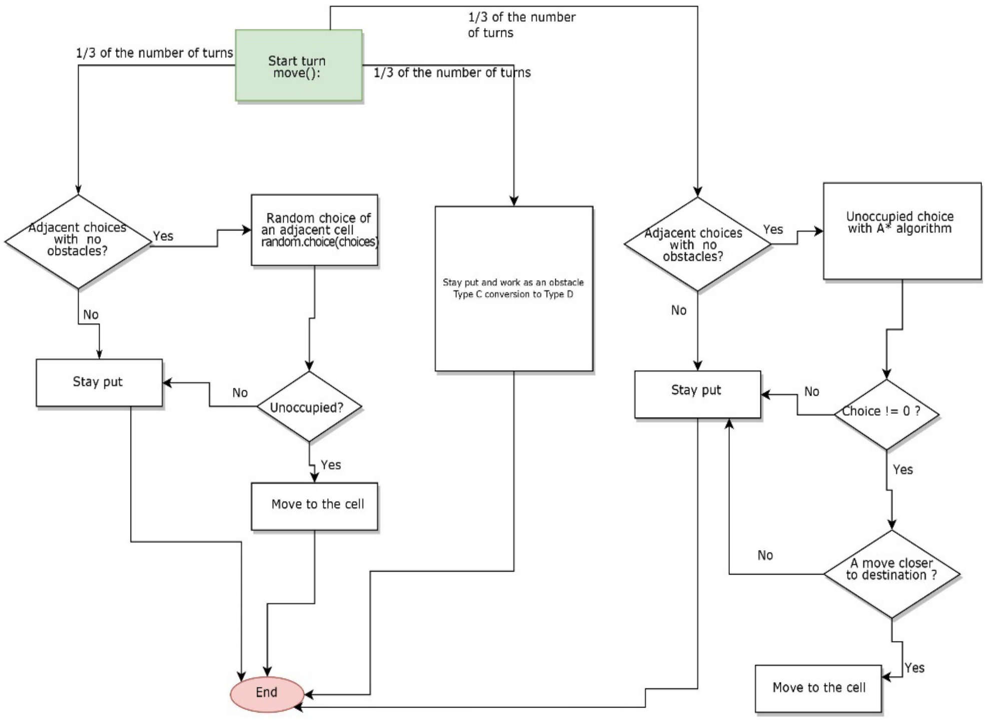


Figure 4: Decision flow chart of Type C agents.

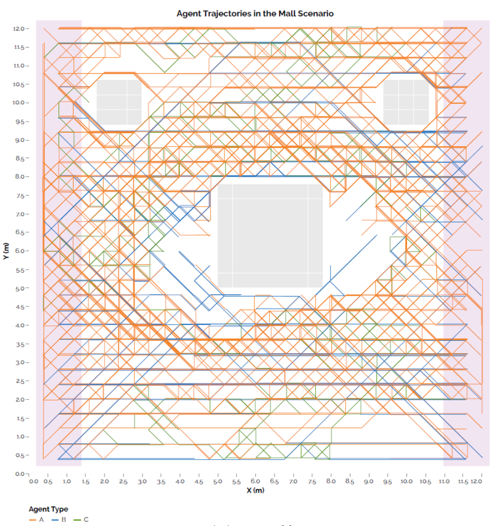
4. SCENARIO SIMULATION

Since the main objective of this study is to develop a simulation using a three-tiered heterogeneous agent classification with the notion of moving and stationary obstacles and a unified model that mimics time and distance conscious walking behaviour and apparent behaviour of pedestrians, we focused on studying how these behavioural differences affect the fundamental parameters of movement and these agent types use the space during a crowded situation.

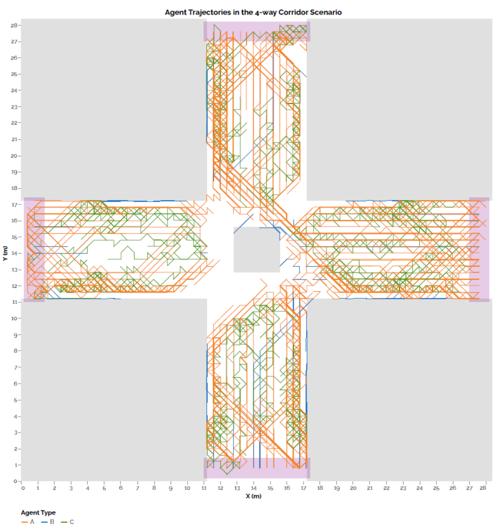
4.1. Scenario Definition

To capture the effects of the heterogeneous mixture of pedestrians and their interaction with various geometries, three grid configurations outlined in Table 2 were studied. In each scenario, two mixtures of agents were considered, a low-tourist mix with 10:7:3 (A:B:C) ratios, and a high-tourist mix with 7:3:11 (A:B:C) ratios of pedestrian types. Additionally, for each grid configuration and mixture, the target density for the simulation was tested in increments of 5% cell occupancy, ranging from 5% to between 40% and 50% depending on the ability of the simulation to reach these higher density rates.

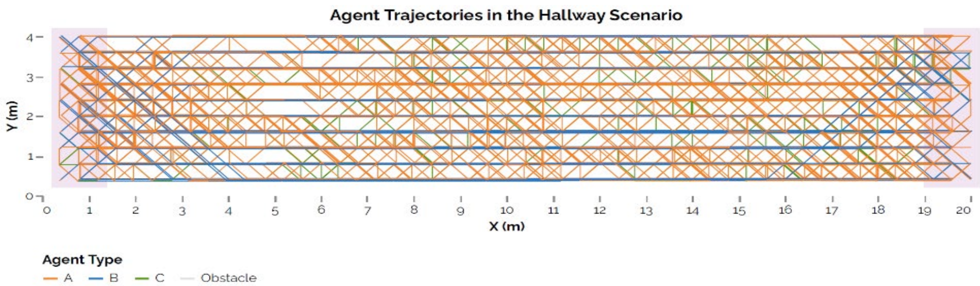
The “mall” scenario consists of a square grid approximately 144m^2 in area, representing a common area of a shopping precinct. A vertically asymmetric set of obstacles is placed to create disruptions for pedestrians and can represent features such as fountains, occupied areas for events, shops, and small booths, as is commonly seen in a mall. Approximately 7.5% of the grid space is taken up by obstacles. Agents are spawned on the left and right sides of the grid (Figure 5a) and are given a random destination on the opposite side. The top and bottom boundaries act as walls. The “hallway” scenario can represent a hallway, elevated pathway, wide crosswalk, or underground transfer tunnel between metro stations. The grid is 4m wide and 66.5m long. Agents are spawned at the left and right sides of the grid (Figure 5c) and given a random destination on the other side. The top and bottom edges of the grid act as walls. In this scenario, the density ρ was increased from 5% in increments of 5% up to a saturation point of 45%, where it became impossible to place enough agents due to the flow of pedestrians across the spawn areas.



(a) Mall



(b) Four-way



(c) Hallway

Figure 5: Trajectories and grid layouts for three scenarios with 30% target density. Only steady-state trajectories shown. Agent spawn areas in pink, obstacles in grey.

The "junction" scenario represents a facility where pedestrians move between four directions in an enclosed space, such as a transfer point on a metro system, an underground pathway system, or an enclosed public square. Direct movement across the junction is blocked by an obstacle representing a decorative feature such as a fountain or a store or booth such as a ticket vendor or convenience store. Agents are spawned in all four directions (Figure 5b), and their destination is chosen randomly from the three other edge areas on the grid.

Table 2: Simulation scenario definitions

Scenario Grid	***W*×*H*** (In cells)	***W*×*H*** (In meters)	Potential Applications
Mall	30×30	12×12	A common area inside a shopping precinct (144m2)
Hallway	50×10	20×4	Hallway, wide crosswalk, or elevated pathway (80m2)
Intersection	70×70	28×28	Intersection in pedestrian pathway; transfer point on metro line

In calculating the density and the speed of agents, classical methods discussed by Blue and Adler [14] and Yue et al. [23] were leveraged. According to this method, the density ρ is defined as the number of agents N, divided by the total number of cells that can be occupied (W×H minus obstacles). The speed was measured by the total number of moves made by agents, divided by the total number of agents on the grid at that time step. Average velocities over the course of the simulation for all three agent types were collected separately. For the hallway scenario, a maximum target density of 45% was reached before the flow of agents made the simulation unable to spawn enough new agents in empty cells. For similar reasons, the maximum target density reached for the four-way intersection was 40%.

5. RESULTS AND DISCUSSION

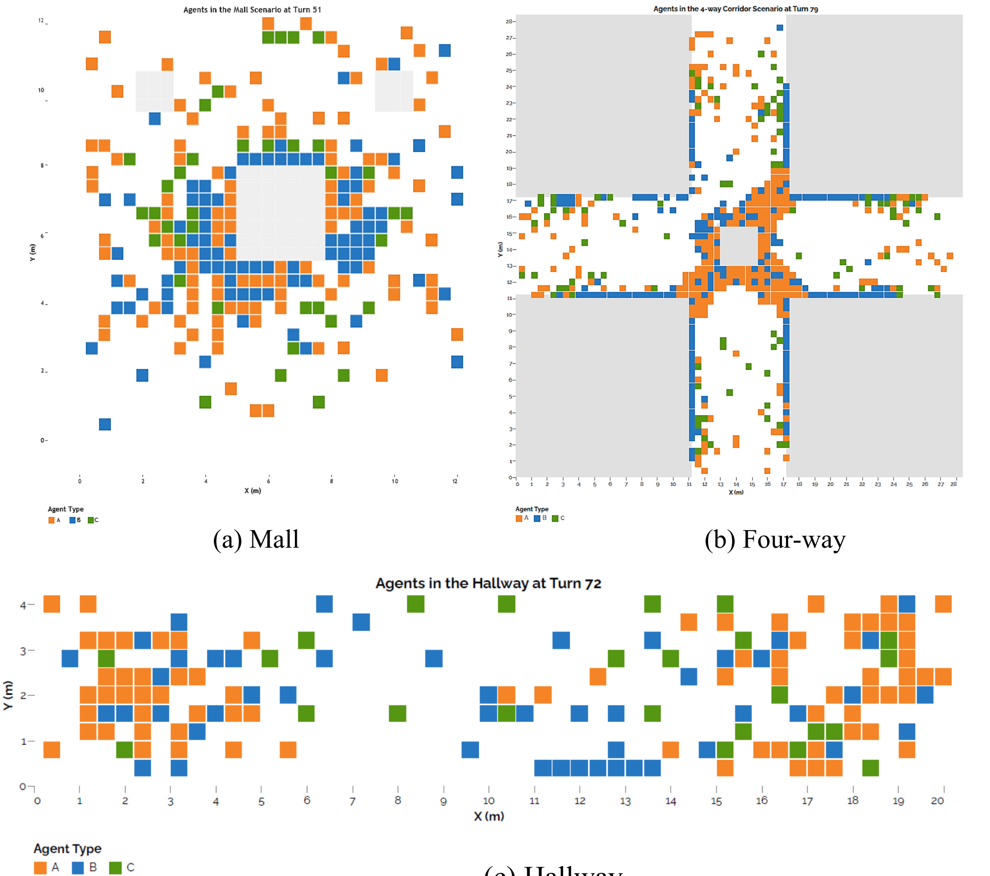
This section reports on and discusses the results of the simulated scenarios, noting individual characteristics and observations in various scenarios and by examining aggregate results. We begin with a discussion on phenomena observed inside the simulation runs themselves, discussing their replication of heterogeneous behaviour and implications of the simulation runs. We then discuss the relationship between speed and density, as well as flow and density. Summary results for each scenario are given in Table 3, and summary speed-density and Flow-density diagrams for the six scenarios are shown in Figure 8 and Figure 9. Figure 10 shows the average fraction of the three types of agents whose velocities were zero (stopped) during the simulation at various densities and mixtures. For each scenario, we report the trajectories of all agents throughout the steady-state simulation and the position of agents 20 turns after the steady-state phase of the simulation was reached. Trajectories and agent positions are coloured by agent type. To better visualise overlapping trajectories that shared the same paths, each trajectory was assigned a random “jitter” of 8% of the cell width. Areas of the grid with thicker lines indicate a higher volume of trajectories passing through that area.

Table 3: Summary of key simulation results

Scenario (Type C Mix)	Type	**Max Speed (m/s)**	**Flow (moves/s)**		Idle Jump
		(at ρ = 5%)	Max	ρ (%)	ρ (%)
Mall (High)	A	0.99	59.5	45	-
	B	0.87	23.5	35	35
	C	0.59	55.3	45	-
Mall (Low)	A	0.97	79.3	30	-
	B	0.85	31.5	45	-
	C	0.62	18.9	50	-
Hallway (High)	A	0.98	32.5	30	25
	B	0.99	14.6	25	25
	C	0.55	35.7	45	-
Hallway (Low)	A	1	66.9	30	30
	B	0.94	39.9	30	30
	C	0.53	15	45	-
Four-Way (High)	A	1	123.1	30	20
	B	0.98	34.6	35	20
	C	0.59	114.6	40	-
Four-Way (Low)	A	1.01	121.3	20	20
	B	0.84	73.2	20	20
	C	0.62	37.6	35	-

5.1. Clustering and Lane Formation

Type Bs typically keep their movement in a straight line, minimising their walking distance by limiting deviations from the shortest path. This can be seen in Figure 5a and 5c, contrasted with Type A movements which involve more adjustment. The “zigzag” behaviour of Type As can be seen in Figure 5c, with a large number of diagonal movements in the centre of the grid made by Type A agents. The random movements and high degrees of freedom in movement choice of Type Cs are apparent examining sample trajectories in Figure 7. Cluster formation around obstacles was observed in the mall and four-way scenarios, indicated by the density of trajectories in Figure 5a and 5b and the collection of agents around the central obstacles in Figure 6a and 6b. These clusters were mainly observed for Type A agents. Lane formation occurred in all scenarios but is most clearly visible for Type B agents in the four-way scenario (Figure 6b). These lane formations resulted in rows of agents following each other toward the same exit area. This lane formation is less visible for Type As as they move first in turn and choose to move around queues of individuals. The random choice of turn order within a class of agents means that some Type B agents will remain stationary if their chance to move occurs ahead of the agents in front of them. This results in longer queues for Type B agents to form. Smaller versions of these queues and diagonal clusters of similar behaviour are seen in Figure 6c and 6a.



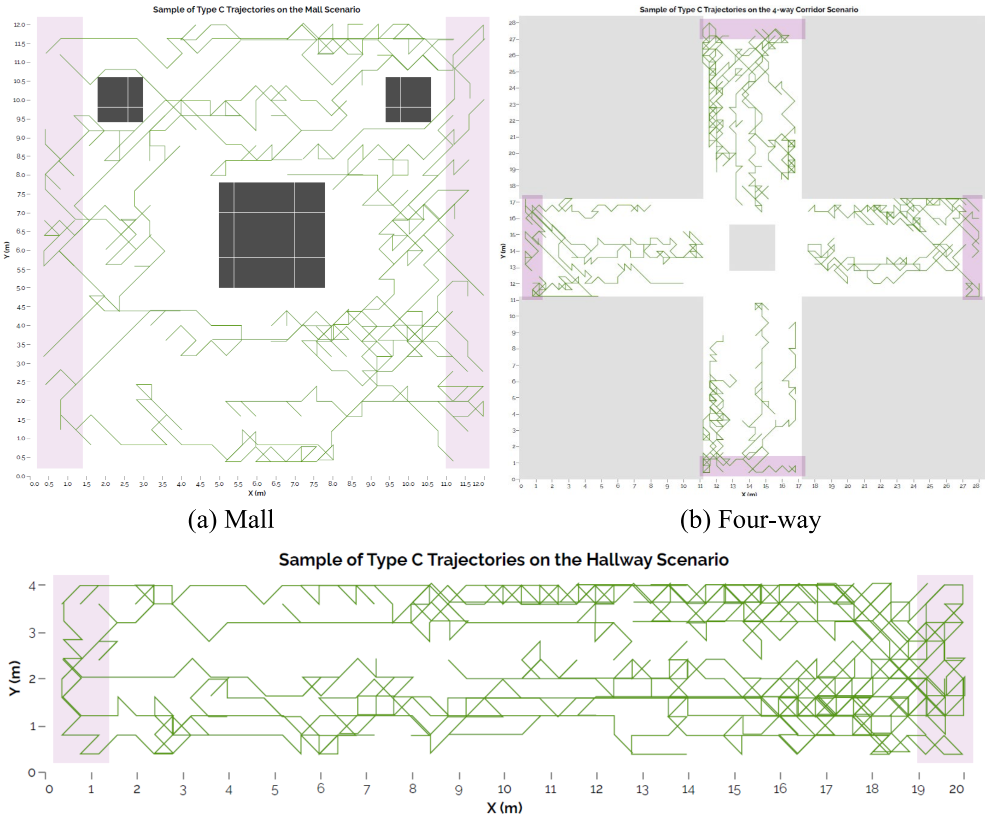
(a) Mall

(b) Four-way

(c) Hallway

Figure 6: Position of agents 20 turns after steady-state for low-tourist scenario and a target density of 30%

Type A agents were always faster to reach their destination and leave the grid, even with interactions with slow moving Type C agents or stationary obstacles. The strategy of continued movement appears to result both in a greater overall speed (as movement is near constant for Type A agents) but also a faster straight-line speed from origin to destination. This corroborates the model’s intent to capture time-conscious behaviour in Type A agents.



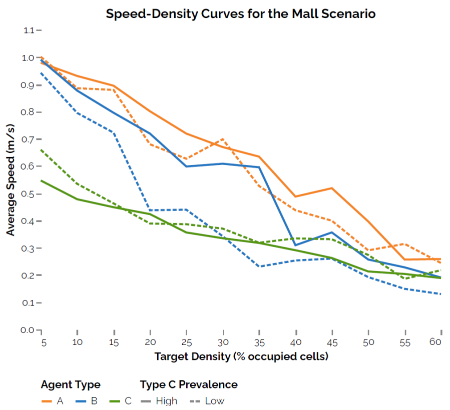
(a) Mall (b) Four-way

(c) Hallway

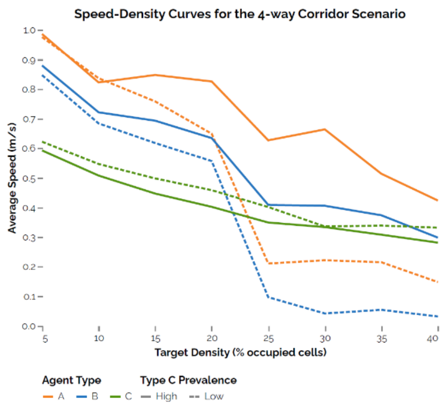
Figure 7: Sample trajectories (30) of Type C agents' movement on the grid during the steady-state simulation phase

5.2. Speed, Density, and the Mixture Effect

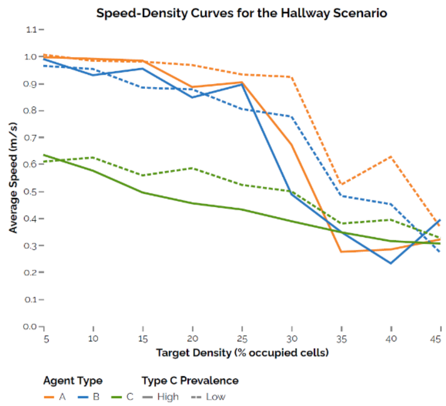
As discussed in Section129 4, in order to understand the effect of heterogeneity among pedestrian behaviours, two mixtures of agent types were considered: A low-tourist mix with 10:7:3 (A:B:C) ratios of pedestrian types, and a high-tourist mix with 7:3:11 (A:B:C) ratios. Under the mall and hallway scenarios with a lower ratio of tourist-type agents, Type A speeds were observed to be higher for all densities. Inside the four-way grid, speeds of both agent types As and Bs get overtaken by Cs at a density of 23% (See Figure 8 and Table 3). As shown in Figure 9, a significant capacity drop for Type A and B agents was observed within all lower mix-grid scenarios, yet only Type C agents seem to have no impact when densities get higher inside both the hallway and four-way grids. Inside the four-way low tourist ratio grid, As and Bs were steadily impacted by increasing density, where both agent types' agent speeds dropped by almost 40% after hitting the 20% density mark. Further, Type Bs reach their jam density approximately at 40% within the same four-way grid.



(a) Mall



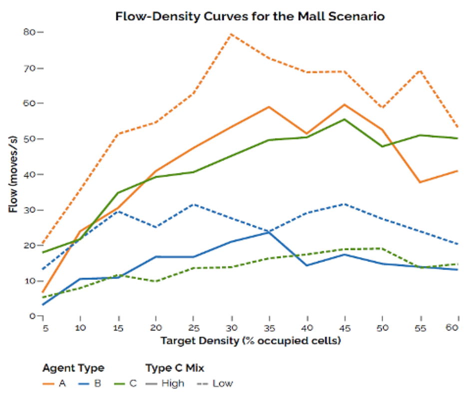
(b) Four-way



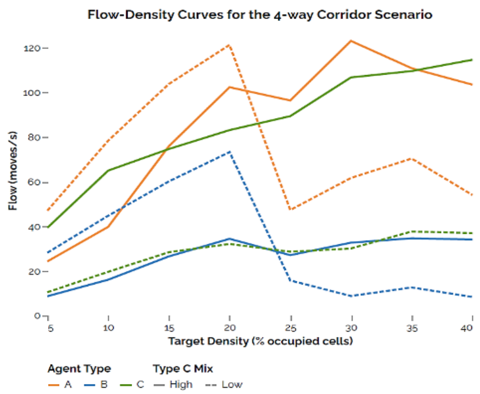
(c) Hallway

Figure 8: Speed-density charts for simulation runs under the three scenarios

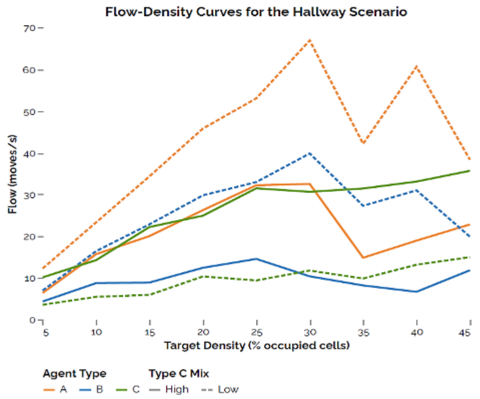
For the higher tourist mix scenarios, the speeds of Type A agents are only lower than the other two types inside the hallway grid after reaching a density of ρ = 35%. Nevertheless, a significant capacity drop was not observed for Type Cs inside the hallway grid and both Bs and Cs inside the four-way grid. Type A agents tend to use the extra unoccupied space by moving, keeping their average speed (0.65 m/s for all scenarios) above other types almost all the time and inside all grids. This could be explained as taking detours or overtaking others using the additional space to move faster. Agent Bs kept their average speeds (0.53 m/s for all scenarios) in between As and Cs (0.40 m/s for all scenarios) for almost all the cases, where the pedestrian densities were below ρ = 30% to 35%. When the tourist mixtures are compared, both Type As (High: 0.67 m/s; low:0.63 m/s) and Bs (High: 0.58 m/s; low: 0.49 m/s) were observed to have higher average speeds when the Type C presence is higher. However, this is the opposite for Type Cs, where with a higher tourist mix, Cs were observed to have lower average speeds (reduced by 5% on average) compared to the lower case.



(a) Mall



(b) Four-way



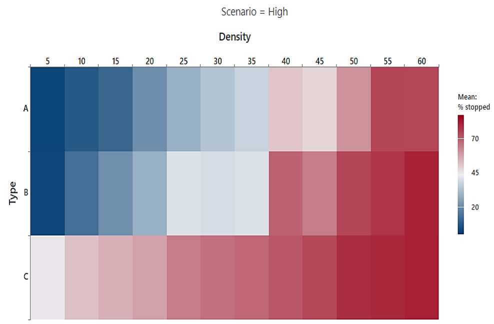
(c) Hallway

Figure 9: Flow-density charts for simulation runs under the three scenarios

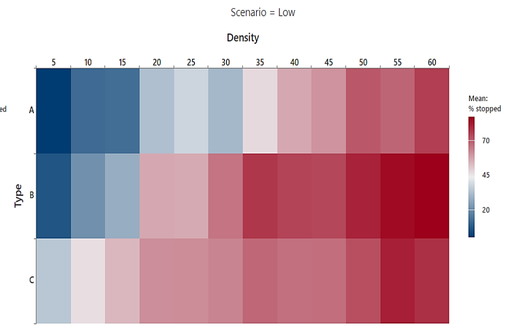
5.3. Idling

In this simulation, idling can be defined in two ways: voluntary idling, which is an embedded characteristic of Type C agents, and forced idling, when agents have no movement options and remain stationary. We consider agents in both these situations to be "idle agents" and show the percent of stopped agents by type in each scenario in Figure 10. This rate is calculated as the total number of turns that agents of a given type that were stationary divided by the total number of turns the agents were given throughout the simulation.

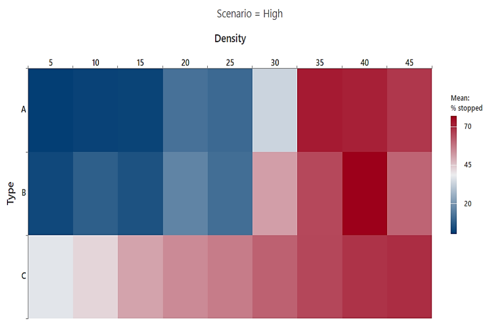
As shown in Figure 10, the idling characteristics of Type C agents are clearly visible at lower densities. Type B agents were the first affected by increasing density, and Type A's were relatively unaffected until higher densities were reached (30 to 35%). Inside the mall grid, Type Bs were the most affected by the increased number of tourist-type agents, and more than 50% of the Type C agents sat idle even at 20% density. A higher number of tourists in the hallway grid reduced the amount of stopping required by Type A and B agents, suggesting that an increased tourist mix decreased the amount of interference between the two pathfinding agents. In the four-way grid, the increased number of Cs made the movements of both As and Bs more constrained, pushing Bs toward to their jam density more rapidly compared to the low-tourist mix condition.



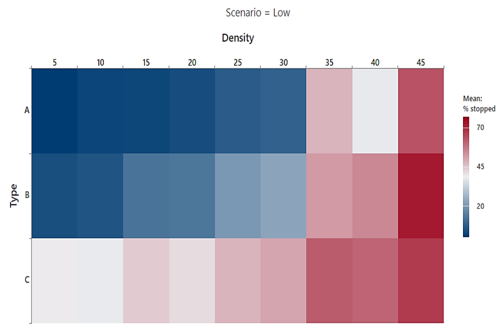
(a) Mall (low-tourist mix)



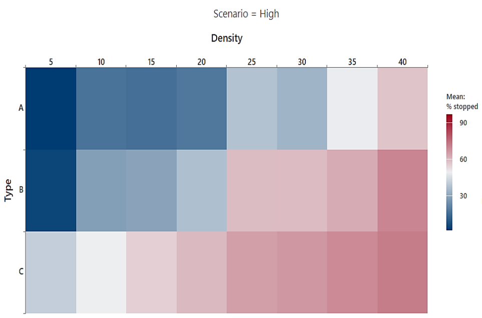
(b) Mall (high-tourist mix)



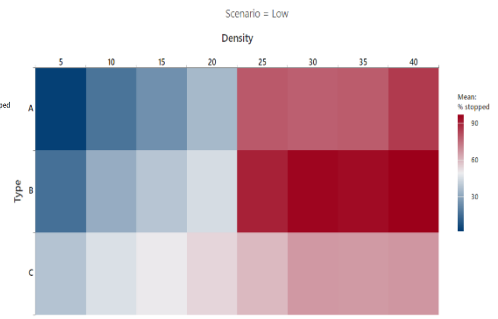
(c) Hallway grid (low-tourist mix)



(d) Hallway grid (high-tourist mix)



(e) Four-way grid (low-tourist mix)



(f) Four-way grid (high-tourist mix)

Figure 10: Heat maps of zero velocity percentage variations with density

6. SUMMARY OF FINDINGS AND POLICY IMPLICATIONS

For all three types of agents, the speed-density curves were consistent with earlier simulation studies, especially those which used CA-type grid space pedestrian facilities where the average speed of all agents tends to decrease as the density increases (linear relation), and the average flow rates tend to reach a maximum exhibiting concave function characteristic. Type A, B, and C agents' average free-flow speeds (maximum speed noted) were 1.0 m/s, 1.0 m/s, and 0.66 m/s, respectively. Simulation results from Blue and Adler [14] and Ali et al. [8] show a similar range of mean free-flow speeds and speeds at the capacity that aligns with the real-life scenario investigated by Rastogi et al. [26].

The mall grid exhibits the most clearly visible macroscopic characteristics, with all agents having a capacity drop and comparative speeds according to assigned rules. The four-way shows the most intriguing results, where Types A and B struggled to achieve the intended speeds with the low-tourist mix. This might result from having more sharp turning movements with obstacles compared to the other two cases. Type A agents were the most affected inside the low-tourist four-way situation, with an approximate 30% drop in the average speed at $\rho = 40\%$ compared to the higher-tourist mix. This implies that having more homogeneous agents can cause interference within agent types. Having more tourist-type agents made movement easier for Type Bs inside the four-way grid exclusively without a significant capacity drop.

In all cases, Type B showed initial speeds higher than those of Type C agents, but this was different and diminished at a density of 25%. Minimising distance resulted in more turns spent stationary, which occurs more frequently when the grid gets more populated. On the other hand, Type Cs acted as moving obstacles for Bs, making it hard to move in the presence of a higher tourist mix. In this simulation study, real-life pedestrian characteristics such as lane and cluster formation, avoiding collisions, slowing down, step-and-slide manoeuvres, taking detours, overtaking, and idling were observed. The higher presence of As and Bs around obstacles in our examples was the result of agents trying to minimise their time and distance by taking the shortest route if possible, producing more diagonal and sharp bending routes.

By introducing a three-tiered behaviour system, we gained insights into how much time-conscious, distance-conscious, and tourist-type pedestrian behaviour affects movement patterns. Heterogeneous characteristics had a more significant impact on free flow speed, average speed, and the capacity of pedestrian walking facilities. We found that introducing "wandering" or "tourist" type pedestrians had a more significant impact on the speeds of those who try to minimise time and a more significant impact on those who try to minimize the distances (seniors, those with mobility challenges, pedestrians with luggage, or heavy clothing) by compelling them to stay stationary for more extended periods of time.

Due to such diverse impacts of pedestrian behaviours on urban flows, our research findings highlight the importance of fostering inclusive urban environments for different types of pedestrians. Adopting adaptive infrastructure such as pedestrian scramble crossings and intelligent traffic signals can optimize the time spent by Type A pedestrians navigating city streets. It is also imperative to adopt tactile paving and universal design principles to ensure safe and accessible navigation for Type B pedestrians, including those with disabilities. Alongside physical infrastructure, initiatives such as wayfinding systems (Kiosks) are pivotal. They provide real-time, navigable insights for all pedestrians, thereby democratising urban navigation and enhancing the urban exploration experience of Type C pedestrians by providing clear information.

We also suggest that considering differences in the overall composition of pedestrian types can influence building design. For example, a train station that serves primarily commuters might design spaces to accommodate flexible route finding and movement even along non-shortest-path routes, while connections around hospitals or senior's residences might focus instead on providing the highest straight-line capacity possible, even with a reduction in route choice. Areas with large portions of tourists or wanderers should include space for these pedestrians to gather outside of the main corridor (alcoves, benches, inset shopping windows, etc.).

Further, policies should champion stakeholder engagement and public participation, ensuring diverse pedestrian needs shape the urban fabric. Education and awareness programs further this aim, fostering community appreciation for inclusive urban environments.

Lastly, advocating for increased research and innovation funding is vital to sustaining advancements in pedestrian dynamics and urban design, propelling the creation of cities that are accessible, safe, and enjoyable for all pedestrians. These policy implications, grounded in comprehensive research findings, pave the way towards more sustainable, inclusive urban development, where the collective needs of all pedestrians are met harmoniously.

7. CONCLUSION AND FUTURE RESEARCH

In conclusion, our research has demonstrated the significance of incorporating a three-tiered behaviour system into pedestrian dynamics modelling. By categorising pedestrians based on their time-consciousness, distance-consciousness, and tourist-type behaviour, we have uncovered valuable insights into how heterogeneous characteristics impact movement patterns within walking facilities. Notably, our findings reveal that the presence of "wandering", or "tourist" type pedestrians exerts a considerable influence on the speeds of individuals aiming to minimise time or distance.

The utilisation of a cellular automata model has enabled us to address existing research gaps and provide novel perspectives on pedestrian dynamics. Our study delves into the nuanced effects of behavioural differences on fundamental movement parameters, shedding light on how various agent types navigate crowded spaces. This simulation framework offers a practical decision-making tool for walking facility designers, facilitating realistic pedestrian behaviour simulation through a simple set of rules. Additionally, it enables designers to account for slow-moving and stationary obstacles when planning pedestrian environments.

Looking ahead, future research endeavours should extend the applicability of our approach by simulating real-life scenarios within bustling walking facilities, such as airports or busy sidewalks, incorporating a greater diversity of stationary obstacles to validate our results. Furthermore, there is potential for integrating our model into evacuation simulations to explore how individuals interact during emergency situations, particularly by simulating Type C behaviours, wherein agents prioritise searching for loved ones before optimising for time or distance minimisation.

In summary, our agent-based simulation study has yielded intuitive and realistic results by leveraging a three-tiered heterogeneous agent classification, considering both moving and stationary obstacles, and incorporating various pedestrian behaviours into a unified model. This comprehensive framework offers valuable insights for urban planners, facility designers, and emergency management personnel seeking to optimise pedestrian flow and safety in diverse environments.

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