COMMUNITY CHANGE

Communication of Uncertainty in AI Regulations

ARTICLE

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VIRGINIA TECH PUBLISHING

ABSTRACT

Scholarship of uncertainty in artificial intelligence (AI) regulation has focused on theories, strategies, and practices to mitigate uncertainty. However, there is little understanding of how federal agencies communicate scientific uncertainties to all stakeholders including the public and regulated industries. This is important for three reasons: one, it highlights what aspects of the issue are quantifiable; two, it displays how agencies explain uncertainties about the issues that are not easily quantified; and three, it shows how knowledgeable agencies perceive the public audience in relation to the issue at hand and what they expect from such communication. By analyzing AI regulations across four categories of scientific uncertainties, this study found that uncertainty in areas of ownership, safety, and transparency are hard to quantify and hence agencies use personalized examples to explain uncertainties. In addition, agencies seek public input to gather additional data and derive consensus on issues that have moral implications. These findings are consistent with the literature on tackling uncertainty and regulatory decision-making. They can help advance our understanding of current practices of communicating science effectively to explain risks and uncertainties.

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KEYWORDS:

Uncertainty; Artificial Intelligence (AI); Notice and comment; Rulemaking

TO CITE THIS ARTICLE:

Phutane, Aditya Sai. 2023. "Communication of Uncertainty in AI Regulations." *Community Change* 4(2): 3. DOI: https://doi.org/10.21061/cc.v4i2.a.50

DOI: 10.21061/cc.v4i2.a.50

INTRODUCTION

A key challenge in regulating emerging technologies is communicating different types of uncertainties to the public and stakeholders affected by regulations. This is partly owing to the unavailability of information in the initial application of the technology. Another factor is the varied goals of regulating agencies, such as seeking input from experts and consensus from the public. This study explored two research questions in the context of Artificial Intelligence (AI) regulations:

1. How do regulating agencies communicate different types of uncertainties in the application of AI?
2. How do agencies' communication goals vary by different types of uncertainty?

Scholars have found evidence that members of the public identify with a personalized narrative whereas experts are concerned with generalizable results and numbers (Sandman and Lanard 2003). Hence, most of the scholarship is devoted to understanding when, how, and why trust in communication varies when it is represented in numeric versus textual forms (Lowrance 1976; van der Bles et al. 2020; Hendriks and Jucks 2020; Kreps and Kriner 2020).

However, uncertainty furthers the issue of communication since there is no consensus on ideal ways of representing or quantifying it. Instead, communication is largely mediated by the goals of organizations, such as the case of bureaucratic communication in the form of regulatory texts by federal agencies.

For example, in a study of uncertainty and risk communication, Krebs (2011) described the case of the UK's Food Standards Agency's public notice on the carcinogenic effect of dioxins linked to funeral pyres of cattle suffering from foot-and-mouth disease, which may have spilled into pastures and contaminated a small percentage of dairy products. There was no way to quantify or measure the degree of risk posed by the spillover, but external scientific experts and the Food Standards agency had differing goals. The government agency wanted to delay communicating uncertainty to avoid public frenzy whereas scientific experts wanted to provide the public with information on the uncertainty of the risk and alternatives in the worst-case scenario.

This article analyzes notice and rule texts to understand how regulating agencies communicate different types of scientific uncertainties associated with the application of AI. AI refers to the science and associated products that perform tasks that otherwise would be attributed to human intelligence (ANSI INCITS 172-2002 2007).

Several uncertainties surround the application of AI due to the wide-ranging implications and lack of transparency into the inner workings of AI models (Bhatt et al. 2021). A common example underlying several applications of AI is the lack of transparency in identifying and acknowledging the biases in the technology's training data. For example, oximeter measurements have been found to miss detection for Black patients (Sjoding et al. 2020), algorithms recognizing symptoms of cardiac conditions were found to be heavily trained on data from male patients, and facial recognition used by law enforcement was found to report false positives for Black women (Sjoding 2020). Without transparency regarding how algorithms make decisions and the quality of the data on which they are trained, there will always be uncertainty in the outcomes.

In controversial policy domains such as criminal justice and employment, scholars have proposed that public mistrust may arise from the convergence of algorithmic opacity and the resulting discriminatory outcomes. Consequently, they advocate for enhanced public engagement and third-party audits as means to educate the public more effectively (Kroll et al. 2016). Additionally, some authors argue that transparency alone is insufficient and emphasize the importance of incorporating explainability, interpretability, and improved representation of uncertainties in AI algorithms (Surden 2019; Sacha et al. 2016; Hendriks and Jucks 2020). How such uncertainties are communicated can also shed light on different proactive or reactive approaches that agencies can take in response to the adoption of AI technology (Grundfest 2001).

One issue identified by scholars in the communication of uncertainty is the inherent skepticism with which the public views scientists and government institutions. This skepticism can lead to different outcomes, such as the tendency to overestimate risks when scientists communicate findings, or the inclination to underestimate risks when expressed by government institutions. For example, a study conducted by Johnson and Slovic (1998) explored an experiment focused on communicating information about carcinogens in water. The research revealed that in certain cases, the public tended to overestimate the risks associated with these carcinogens based on the information provided by scientists.

Similarly, in the context of the COVID-19 pandemic, there has been a notable tendency for some individuals to underestimate risks due to their belief in conspiracy theories. Farias and Pilati (2023) investigated this phenomenon, highlighting how conspiracy theories have led some individuals to downplay or disregard the risks associated with the pandemic, despite evidence presented by government institutions. In the COVID-19 context, accepting and acknowledging uncertainty was found to generate public skepticism initially. However, researchers Kreps and Kriner (2020) suggested that this acceptance of uncertainty can ultimately serve as a safeguard against potential disbelief when new findings emerge that contradict initial knowledge.

These studies demonstrate the complex relationship between communicating uncertainty, public skepticism, and risk perception. Understanding and addressing these dynamics is crucial for effectively conveying uncertain information to the public and fostering informed decision-making. Researchers in food and environmental regulation have also investigated the purpose of organizational communication and chosen audiences (Lofstedt, McLoughlin, and Osman 2021; Beck et al. 2016). By extending this line of inquiry into AI, this research contributes to understanding how government agencies identify and communicate uncertainties in an area of emerging technology that is riddled with contrasting opinions from the scientific community.

Each case highlights the importance of prior beliefs and organizational goals in communicating uncertainty. How organizations justify their communication of uncertainty is just as crucial as how they communicate potential risks to the public. A case in point is a survey conducted by Fischhoff (2013) concerning the risk of fatalities from avian flu. The survey revealed that medical experts, aiming to allow for a wide margin of error, expressed the risk verbally. However, technology experts who focused on preparing for worst-case scenarios relied on numeric likelihood estimates.

How uncertainty is expressed is useful in establishing trust between government institutions and the public. Experimental evidence suggests that while numbers and text are useful for communicating uncertainty, text slightly reduces trust in numbers but not in the source providing that information. Trust and transparency have been shown to be key factors that influence the effect of thoroughness, accuracy, and convenience of information on uptake of government services (Venkatesh et al. 2016). In addition, past studies also highlight the importance of how this information is transmitted, whether point-estimates or confidence intervals (CI) are provided, whether ranges are expressed as numbers and if they start with zero as base-level or whether text is used to describe or provide succinct answers to questions of risk and uncertainty (van der Bles et al. 2020; Hutmacher, Reichardt, and Appel 2022; Fischhoff 2013).

Opinions on AI have been polarized in the public imagination, partly due to its depictions in pop-culture and lack of consensus among scientists developing the technology. Some have also proposed that AI merely regurgitates information using data that is not trained using a representative sample and that does not reflect their values (Allison 2023). The challenges associated with explaining the process and inner workings of AI, coupled with the lack of publicly accessible resources that elucidate how AI applications function and their limitations, underscore the crucial role of regulations in bridging this gap. This position has been reiterated by technologists and CEOs concerned with governance of AI technology, especially with regard to the robustness and transparency of the AI algorithms (Bhuiyan 2023; Blouin 2023). Scholars have also found that publicly-accessible, large language models such as ChatGPT have made it harder to differentiate between AI and human generated content (Solaiman et al. 2019; Goldstein et al. 2023). Key to this process is addressing the uncertainty and debates among scholars in a way that the public can comprehend. How agencies transmit this information is the first step to this process that is addressed in this research.

DOI: 10.21061/cc.v4i2.a.50

There is debate among scholars and practitioners on how to align scientific and public policy goals with appropriate communication (National Academies of Sciences, Engineering, and Medicine 2017, 80–85). These goals can range from defining the science of an issue for the public to planning actions addressing scientific uncertainties. By categorizing variations within such a continuum, this article sheds light on the priorities of several independent, executive branch, and standard-setting agencies to address each type of uncertainty. The federal agencies included for analysis are the National Highway Transport and Safety Administration (NHTSA), Consumer Product Safety Commission (CPSC), Food and Drug Administration (FDA), Patent and Trademark Office (PTO), Department of Education (ED), National Institute of Standards and Technology (NIST), and Office of Science and Technology Policy (OSTP).

This study's conceptualization of uncertainty is inspired by three key pieces of scholarship. First, Walker et al. (2003) developed a framework for mapping uncertainty based on three key parameters: location, level, and nature. Here, uncertainty is defined as "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system" (Walker et al. 2003, 8). Second, van der Bles et al. (2019) proposed a framework for communicating epistemic uncertainty (i.e., *known unknowns*). Uncertainty is conceptualized as the limitations of knowledge and science in their ability to quantify risks. Third, a report detailing how the EPA makes decisions in the face of uncertainty refers to uncertainty as "variability and heterogeneity due to lack of information" (IOM 2013, 39). This study draws from this set of literature to build four categories that frame the types of uncertainties in AI application: *probabilistic, model, deep,* and *moral uncertainty.*

Probabilistic refers to naturally occurring uncertainty and manifests in the datasets used in training AI algorithms. This category is inspired by literature on aleatory uncertainty (Walker et al. 2003).

Model refers to uncertainty in the design and modeling of systems and manifests in the supervised and unsupervised models used in AI. Several disciplinary perspectives have accounted for this type of uncertainty under different terms such as epistemic or model, but they point to the same construct and that of uncertainty in models designed to gain knowledge and determine cause-effect relationships (Walker et al. 2003; van der Bles et al. 2020; Hora 1996; Kreps and Kriner 2020; Pavlyuk et al. 2017).

Deep refers to the lack of knowledge, measurement tools, and prediction capability of the consequences of AI applications. The concept has been described as "the condition in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes" (Walker et al. 2003, 919). Others have described it as extreme cases such as worst-case scenarios that are unpredictable or unknown (Sunstein 2020; Beyleveld and Brownsword 2012).

Last, *moral* refers to uncertainty in how AI affects individual and societal values. A comparison between conventional AI language models trained using top-down rules and those trained on the collected data from expert discussions to mimic human moral reasoning revealed notable differences. Specifically, the former models demonstrated an inability to navigate ethical dilemmas such as rating the decision to cause a nuclear explosion to save your child as a "good" decision (Jiang et al. 2022). This highlights the potential of existing moral uncertainty in conventional AI systems used for decision-making. Other scholars have attempted to measure and conceptualize moral and ethical dimensions in the application of AI to the health and transportation sectors (Martinho, Kroesen, and Chorus 2020; Saplacan, Khaksar, and Torresen 2021; Wang et al. 2022).

The following article provides a concise overview of the research on scientific uncertainty types pertinent to AI applications, diverse communication approaches for uncertainty, and the significance of these aspects. The subsequent section will present the framework that serves as the foundation for this paper. Next, the data sources and analysis methods employed will be examined. Lastly, the results and major discoveries will be thoroughly evaluated.

DOI: 10.21061/cc.v4i2.a.50

MAPPING THE SCHOLARSHIP

UNCERTAINTY TYPES AND THEIR RELEVANCE TO AI

Early literature on quantification of uncertainty highlights two types: *aleatory* and *epistemic*. *Aleatory* uncertainty is that which is inherent in data and happens by chance or probability whereas *epistemic* uncertainty refers to the lack of knowledge, methods, or models among scientists and subject matter experts (Hora 1996). These two categories overlap and have found renewed relevance in AI applications where there is aleatory uncertainty in training data and epistemic uncertainty in machine learning models.

Walker et al. (2003) took a broader approach and developed a classification scheme for uncertainties concerning outcomes of scientific models based on *location*, *level*, and *nature*. *Location* encompasses the inputs, parameters, and environmental factors affecting the model. *Level* points to the accuracy range with which the model can predict between determinism to complete ignorance. *Nature* refers to the cause of uncertainty, which may be naturally occurring, or part of the knowledge used to build the model. While this classification is extensive, it is not sufficient for regulators who are concerned with policy implications.

Probabilistic uncertainty is interchangeable in this research context for aleatory uncertainty since it stems from the propagation of incorrect or biased baseline measures or training data. A relevant example is the crime rate in the training data used from some cities to predict housing prices using an AI algorithm (Sattigeri 2021). Crime rates do not exist in isolation and are often a result of criminalization of gentrified neighborhoods. As a result, these neighborhoods receive higher emergency calls and are subject to frequent law enforcement patrols (Sampson 2019). Hence, existing crime rates are symptomatic of gentrification over the years and using crime rate data to train algorithms not only exaggerates societal ills, but also perpetuates uncertainty in crime rates into the future value of neighborhoods.

Uncertainty can also come from a lack of better models or incorrect estimation of model parameters. Model uncertainty in AI applications is often the concern in reinforced learning and is represented using confidence intervals in graphs and tables (Depeweg et al. 2017). Model uncertainty for this research is analogous to epistemic uncertainty since they are both concerned with uncertainty due to lack of knowledge on how well the AI models predict or evaluate causality (Senge et al. 2014). Hence, model is an umbrella term for this research project that represents all aspects of uncertainty in models, such as estimated parameters and predicted outcomes or causality. One way to differentiate this from probabilistic uncertainty is that model uncertainty can be resolved by using additional data whereas the former cannot (Der Kiureghian and Ditlevsen 2009).

Deep uncertainty is the third case that is often associated with emerging technologies. Walker, Marchau, and Swanson (2010) characterize deep uncertainty situations as those that lack any means of evaluating or finding alternative solutions. These are typically the "unknown unknowns" that were popularized in the public imagination by Donald Rumsfeld during the Iraq War (DoD 2002). An example cited by Beyleveld and Brownsword (2012) is the uncertainty in evaluating whether there are adverse health effects due to the diffusion of nanoparticles from food packaging, because there is no existing data, and current equipment does not have the resolution to measure this effect. Other similar examples include unknown but catastrophic effects of climate change that cannot be predicted based on current knowledge (Weitzman 2020; Sunstein 2020; Woodward and Bishop 1997).

Last, moral uncertainty is a well-known concept in scholarship on AI and ethics, especially concerning the predictability of AI-based decision-making (Whitby 2011; Allen, Smit, and Wallach 2005; Bello and Bringsjord 2013). In autonomous systems, degree and type of autonomy (i.e., semi versus full) contribute to moral dilemmas (Firlej and Taeihagh 2021). Vehicles are a prime example that are categorized from 0 (no automation) through 5 (fully autonomous) by the Society of Automotive Engineers (SAE). Accountability for semi and fully autonomous vehicles (levels 3–5) varies between the driver and algorithms depending on whether vehicles have conventional driver seats and the degree of manual controls. This can lead to questions over who is liable for accidents between the driver and manufacturer (IOM 2013; Wang et al. 2022).

Another example of moral uncertainty underlies understanding of the impact to privacy and humanization—that is, making robots seem human to their users such as in the caretaking industry—when AI-powered robots are employed for care of the elderly (Saplacan, Khaksar, and Torresen 2021). A closely related term is *ethical* uncertainty conceptualized by Rossi (2018) and Morley et al. (2021). This term encompasses three key concepts: trust, explainability, and bias. The authors identify use cases where each of these concepts might apply and the degree of uncertainty that they impose in the application of AI by finding evidence of these principles outlined by major industries and government reports.

The four categories described in this section are not an exhaustive list of uncertainties associated with AI, though they encapsulate a diverse range of scientific uncertainties. While the scholarship on uncertainty in AI applications is extensive, there has been less emphasis on whether and how such uncertainty should be part of bureaucratic communication sent to the public. This is essential because government agencies might have multiple reasons for communicating scientific information to the public. The next section maps the literature in greater detail regarding why risk and uncertainty communication matter in these contexts.

COMMUNICATION TYPES AND THEIR EFFECTS

One of the emerging concepts in risk communication is that of uncertainty with the key focus on contextualizing situations and understanding their effects on people's trust in the legitimacy of institutions. In a recent review, Balog-Way, McComas, and Besley (2020) outline the interdisciplinary nature of challenges and the need for utilizing a wide range of tools–such as emotive approaches using day-to-day, example-driven approaches–for framing communication. Scholars have debated how risks should be communicated to the public and whether uncertainty communication is beneficial. Although the scholarship does not provide any consensus, two broad themes emerge: modes of communication (i.e., numeric and descriptive) and whether such communication promotes transparency and trust in institutions.

Modes of Communication

In support of numeric modes, Fischhoff (1995) argued that when quantified uncertainty is presented along with methodologies used to arrive at values, scientists and the public might benefit. More recently, Fischhoff and Davis (2014) also argued that confidence intervals and probability distributions presented with relevant information are less prone to misinterpretation than verbal expressions. Numeric ranges and confidence intervals have been shown in the literature to confuse the audience when it comes to losses (Johnson and Slovic 1998), possibly because of loss aversion. However, survey experiments spanning different policy areas, such as those conducted in Dieckmann et al. (2017), have also shown that numerical ranges are influenced by prior beliefs of individuals. Other forms of numerical information–such as percents, probabilities, and likelihoods–can lead to misinterpretation depending on whether they are accompanied by verbal descriptions (Budescu, Por, and Broomell 2012) or frequency distribution plots (Teigen, Juanchich, and Riege 2013).

In support of descriptive and example-driven modes of communication, Beck et al. (2016) promoted the use of alternatives to point estimates for communicating toxicity values by the Environmental Protection Agency (EPA). Some of these include providing peer-reviewed references and using visual aids and uncertainty ranges to help improve the audience's trust and understanding. Drawing theories from ethics and risks literature, Roeser (2012) argued for an emotional approach to communicating risk from climate change. Similarly, Slovic et al. (2004) found utility for communication through affective rationality, which includes infusing visual aids with statistics and numerical displays of risk.

Osman et al. (2021) identified different modes of textual communication based on persuading and engaging audiences. The authors argue for the use of text with examples as an optimal way to justify and persuade. Recent scholarship by van der Bles et al. (2020) and Kreps and Kriner (2020) have used a wide variety of categories for representing uncertainty such as percentages, confidence intervals, and textual examples to compare how trust in institutions and science differ by these modes of communication. In addition to this list, Jones (2007) suggested that incorporating the implication of uncertainty as part of the text is also a useful strategy for environmental regulations. This set of literature provides the different modes within numeric and textual communication approaches that are available for communicating uncertainty.

Goals of Communication

The Institute of Medicine identifies a combination of numeric, verbal, and graphical options for communicating uncertainty by the EPA relative to the purpose of the communication (IOM 2013, 185–98). These consist of exchanging ideas, developing common terminology, identifying problems, formulating solutions, and justifying actions, depending on the policy-making phase of the EPA. The last two are prominent during and after implementation, whereas the rest are usually seen during the problem-formulation phase. Regulatory notices used in this research area are usually targeted for seeking information and fall mostly in the problem-formulation phase, whereas proposed and final rules fall into the implementation phase.

Jones (2007) identified consensus-building as a key goal of uncertainty communication. Fischhoff (1995) also argued that bringing together experts and non-experts as partners was the last stage of risk communication. Experts have been found to play a greater role in mitigating uncertainty during regulation (Lavertu and Weimer 2011). Experts and interest groups have been found to lobby harder, thereby leading to policy changes when there is scientific conflict (Yackee 2019). Other goals of risk and uncertainty communication cited in literature include fostering beliefs and increasing transparency and learning (Balog-Way, McComas, and Besley 2020).

Overview of the Regulatory Process in the U.S.

Regulatory plans are published yearly under the “Agenda for Regulatory and Deregulatory Action” under the Unified Agenda posted on RegInfo.gov and Regulations.gov. Rulemaking initiatives help to create awareness of actions planned by regulatory agencies. During the initial stages of rulemaking, agencies typically set-up ex parte communication that involves an exchange of information and gathering of opinions in sometimes formal (e.g., negotiated rulemaking settings) and otherwise informal settings behind closed doors with interested parties such as special interest groups and industry stakeholders affected by the regulations under discussion. Sometimes agencies publish an Advanced Notice of Proposed Rulemaking (ANPRM), Notice—Request for Information, or Notice—Public Meeting on the federal register.

Both ANPRM/Notices and negotiated rulemaking led the agencies to develop a Proposed Rule or Notice of Proposed Rulemaking (NPRM) that is posted in the federal register. Once posted, rules are open for the public to comment with no limitations on who can comment for a period between 30 to 60 days, after which a Final Rule gets published. Proposed Rules contain a summary of the rule as part of a preamble, issuing agency name, contact information, and comment period. Agencies can conduct public meetings and public hearings during the comment period and sometimes also extend the comment period. Agencies can resort to a good cause exception to bypass the public comment stage in case of emergencies and when notice and comment are not deemed necessary or feasible.

Final Rules are based on a culmination of suggestions from experts within and outside federal agencies and comments from the broader public. Unless there are major changes in the Final Rule compared to the corresponding Proposed Rule, agencies publish the Final Rule along with an effective date. This date is typically thirty days after posting the Final Rule. Throughout this process, the Office of Information and Regulatory Affairs (OIRA) reviews rules at two stages — before the Proposed Rules are published and before publishing the Final Rule. Typically, significant rules impacting the economy or concerning critical policy issues require a cost-benefit analysis.

DOI: 10.21061/cc.v4i2.a.50

CONCEPTUAL FRAMEWORK

Based on previous scholarship and specific to the case of AI, the framework listed in Figure 1 was developed. The type of uncertainty is determined mainly from its sources and theories from scholarship such as Walker et al. (2003); Walker, Marchau, and Swanson (2010); and van der Bles et al. (2019). Probabilistic stems from "noisy" or incomplete data, models from parameters and predictability of models, deep uncertainty from lack of clear measure and knowledge, and moral uncertainty arises when the application of science results in social and ethical conflicts.

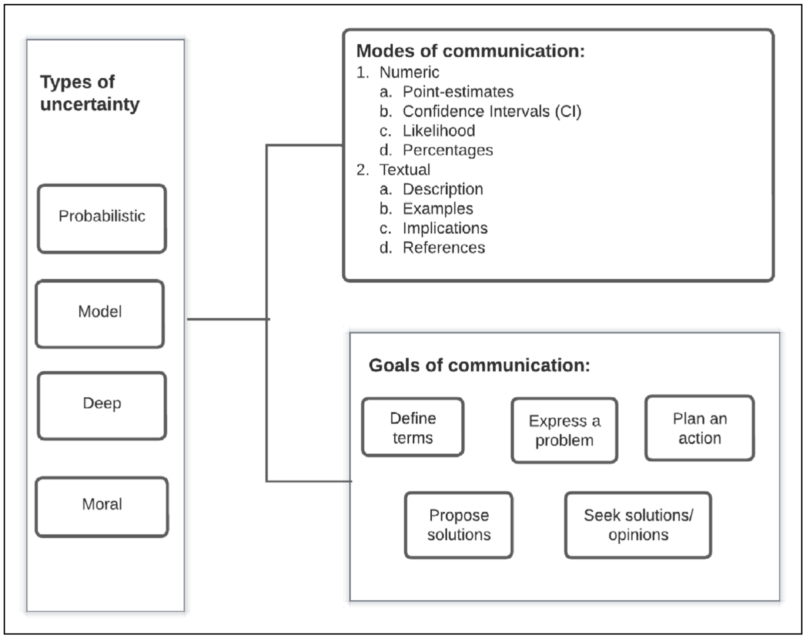

Figure 1 Components of the Research Framework

The modes of communication are primarily classified as numeric or textual. Taking a cue from scholarly work such as van der Bles et al. (2019), numeric mode is further classified into point-estimates, confidence intervals, likelihoods, and percentages. The literature on the textual representation of risk communication has themes such as "risk as feeling" (Loewenstein et al. 2001) with an emphasis on example and implication-driven textual representation of uncertainty. As a result, the textual mode can be subdivided into various categories that address uncertainties effectively. These categories include providing descriptions of the context and terms related to uncertainties, offering relatable examples of situations audiences can connect with to better understand uncertainties, presenting text-based descriptions of potential outcomes, and incorporating references that direct readers to additional sources explaining uncertainty and citing relevant external references such as news articles, trade magazines, and published journal papers. By utilizing these categories, communication efforts can be enhanced to provide a comprehensive understanding of uncertainties. The use of the graphical mode is not employed in this research, and it is important to note that regulatory texts contain a limited number of graphics or visuals. However, it is acknowledged that the absence of graphical representations is one of the limitations of this article.

The goals similarly are derived from the Institute of Medicine (IOM) (2013) and the National Academies of Sciences, Engineering, and Medicine (2017). **Defining terms** is a key purpose behind creating a common terminology, **expressing problems** captures how agencies formulate issues, **proposing solutions** entails possibilities and alternatives, **planning an action** point to executable solutions that are being worked on, and **seeking solutions/opinions** entails instances when there are explicit mentions of public or stakeholder opinions. The next section outlines the data sources used and the method employed to utilize this framework to answer the research questions.

DATA AND METHODS

DATA COLLECTION AND THE DESCRIPTIVE CODING PROCESS

A primary dataset was collected for this project since none currently exist that identify different types of uncertainty in regulatory documents. Textual excerpts from notices and rules were collected and categorized to create such a primary dataset. The primary source for rule text is from the federal regulations website (regulations.gov).

The author narrowed the search term to artificial intelligence. This resulted in 55 proposed rules, 44 final rules, and 250 notices as of April 14th, 2022. A purposive sample of 12 rule documents consisting of 10 notices, one each of proposed and final rules was selected based on whether the rule document (proposed or final) pertained to regulating one or more applications of AI (see supplemental appendix for details).

Any rule documents that did not regulate AI but used the term were not considered. For notices, among those specifically regulating AI, ten random documents were chosen for this analysis. Unlike rule documents, notices including invitations to fora or public meetings that sometimes contain details of regulations were not of interest. Hence, a random sample of notices that involve regulatory information beyond administrative text was chosen. Although this process introduced selection bias, it was purposive in its attempt to capture the most relevant regulatory text concerning a specific application of AI.

The dataset represents eight agencies consisting of four regulatory, two independent, and two non-regulatory agencies. Non-regulatory agencies such as the National Institute of Standards and Technology (NIST) have been instrumental in creating an AI risk framework that is used by other regulating agencies. The Office of Science and Technology Policy (OSTP) has also been issuing public guidance and notices on regulating AI.

Once the raw text was assembled, excerpts from each of the documents were analyzed using a common technique of in-context coding. To do so, the Loughran-McDonald Master Dictionary (LM Dictionary) maintained by the University of Notre Dame was used to narrow words representing uncertainty (Loughran and McDonald 2010). Next, the author inputted the word list obtained along with the rule text into Antconc, a freeware corpus analysis toolkit for concordancing and text analysis, so it could filter-out sentences containing at least one word matching from the LM Dictionary (Anthony 2014). This is part of concordance analysis under Antconc. Appropriate window lengths specifying how much of a sentence or phrase to filter were adjusted. The filtered sentences were read in the context of the surrounding text to manually code for type, mode, and goal of communicating scientific uncertainty. The original excerpt–including single or multiple sentences along with matched words representing uncertainty–was also part of this dataset. The dataset consisted of forty-two excerpts after the filtering and coding exercise. As a robustness check, the entire document was read to look for any additional instances of expressions of uncertainty. Additional relevant excerpts to code were not found. The resulting excerpt-level dataset consisted of 19 excerpts from rule documents (two final and 17 proposed rules), and 23 from the notices.

ANALYTICAL CODING PROCESS

To analyze the text excerpts, inductive and deductive coding processes consistent with scholarship on qualitative coding were used (Moynihan 2008). Uncertainty type was coded first, based on the four categories referenced earlier in this article's conceptual framework. Probabilistic uncertainties were usually worded as inherent or circumstantial (e.g., "varying and unpredictable circumstances" (NIST 2019, 18491)). Conversely, model uncertainties were associated with human-designed models such as in the case of automated driver systems (ADS) that lack steering wheels; this design makes it difficult to test model uncertainty using conventional standards (e.g., "may complicate or may even make [it] impossible to test a motor vehicle" (NHTSA 2018, 2607)). Communication regarding deep uncertainties referenced lack of knowledge or measurement capabilities such as in testing ADS systems where the issue is not just the model of ADS systems but also the lack of understanding regarding how such systems interact with the environment and pedestrians (e.g., "future vehicles with ADS lack any means of human control, it is unclear how the Agency and the manufacturers can conduct compliance tests" (NHTSA 2018, 2609)). Moral uncertainties were inferred from the context (e.g., "Should a company who trains the artificial intelligence process that creates the invention be able to be an owner?" (PTO 2019, 44889)).

Next, texts were coded based on whether numbers or text were used to represent uncertainty. Then, sub-categories within each were coded. Numbers were categorized based on whether they had percentages, confidence intervals, probabilities, or point estimates. For textual categories, most often the coding resulted in the description unless specific examples, references, or implications were mentioned as part of the excerpt. Lastly, one of the five goals was coded. A copy of this dataset was exported into STATA for quantitative analysis after stripping texts of the excerpts. Since the author of this paper was the only coder, there was no way of conducting a reliability test such as Cronbach's alpha, which measures how consistent and closely-related coded constructs are; this is another limitation of the current study. Such a reliability test is often useful when multiple coders are involved and to ensure consistency in constructs.

REPORTING THE FINDINGS

In the results section below, this paper reports on the analysis of distributions of uncertainty type and mode of communication to address the first research question. The second research question was concerned with whether communication goals vary by uncertainty. A convergent, mixed-methods approach was used as outlined in Creswell (2014) where both qualitative and quantitative results are integrated. Quantitative results from STATA are represented in the histograms, whereas the qualitative results are illustrated by sample excerpts from the coding process. The histograms provide overarching patterns regarding different modes and goals of communication by uncertainty type, reinforced and enriched by thematic text excerpts from the dataset.

RESULTS

Figure 2 shows the distribution of excerpts by types of uncertainty. Model uncertainty, followed by probabilistic uncertainty, were the most frequent types of uncertainty encountered in these documents.

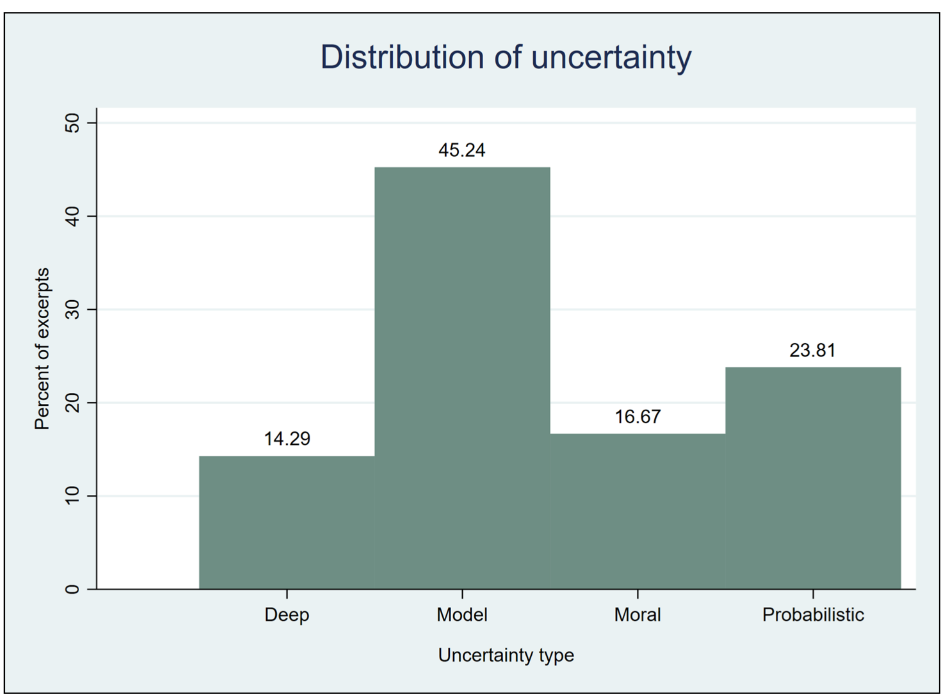

Figure 2 Summary of Excerpts by Uncertainty Type

DOI: 10.21061/cc.v4i2.a.50

MODES OF COMMUNICATION RESULTS

Histograms

The first result in Figure 3 shows the distribution of modes of communication for each type of uncertainty. More than 60% of communication modes for each category of uncertainty were through text. Model uncertainty was the only example where numeric modes of communicating uncertainty were used. These results came from representations of uncertainty when comparing the number of vehicle crashes between AI and manually driven cars. Among textual excerpts, simple text describing the uncertainty was most often used, followed by using examples and use cases to illustrate the implication of uncertainty. Within the scope of this research project, some of the findings from moral and model uncertainty have been illustrated.

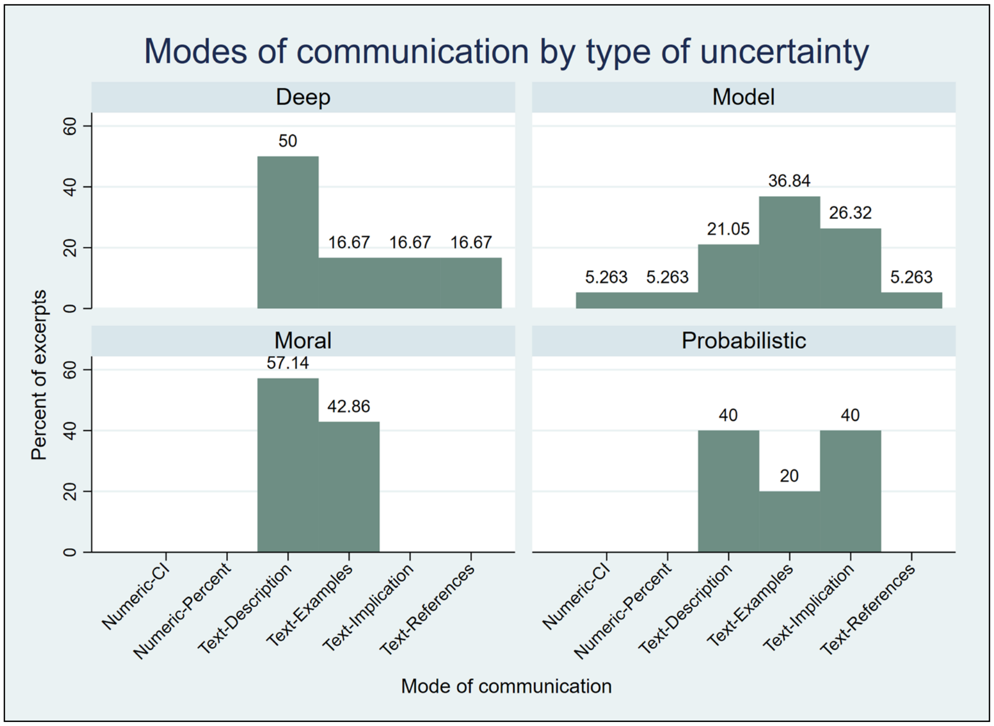

Figure 3 Communication Modes by Uncertainty Type

Excerpts

Examples helped to personalize the communication of uncertainty. Figure 3 illustrates how text examples were a common form for communicating each type of uncertainty (16–42%). This was especially true with moral and model uncertainty. Personalizing with real-world examples intuitively helped readers empathize with the issues in regulating AI applications across a wide variety of sectors. For example, regarding ownership rights and patenting of AI-generated products, this excerpt evidenced the use of real-world examples to address moral uncertainty:

> Should an entity or entities other than a natural person, or company to which a natural person assigns an invention, be able to own a patent on the AI invention? For example: Should a company that trains the artificial intelligence process that creates the invention be able to be an owner? (PTO 2019, 44889)

A second example pertaining to the safety of AI-driven cars embodied model uncertainty:

> Would occupants still need warning telltales and other displays to be viewable if they did not have any means of driving their vehicles? Could there be any risk of adverse safety consequences […]? (NHTSA 2018, 2609)

A third example regarding consumer transparency showed how agencies used fair lending laws to highlight the moral uncertainty in AI applications:

DOI: 10.21061/cc.v4i2.a.50

> Depending on the specific use, there may be uncertainty about how less transparent and explainable AI approaches align with applicable consumer protection legal and regulatory frameworks, which often address fairness and transparency. For example, it may be challenging to verify that a less transparent and explainable approach comports with fair lending laws [...]. (FDIC 2021, 16841)

Moral uncertainty examples, such as those related to patenting above, and the level of transparency required with AI applications, both highlight the agency's indeterminate position and the need for public input when such moral ambiguity is encountered.

COMMUNICATION GOALS RESULTS

Histograms

Figure 4 shows the distribution of communication goals by each type of uncertainty. Seeking public input was a consistent goal across all types of uncertainty. Recent evidence on the role played by comments on final rules attests to this trend.

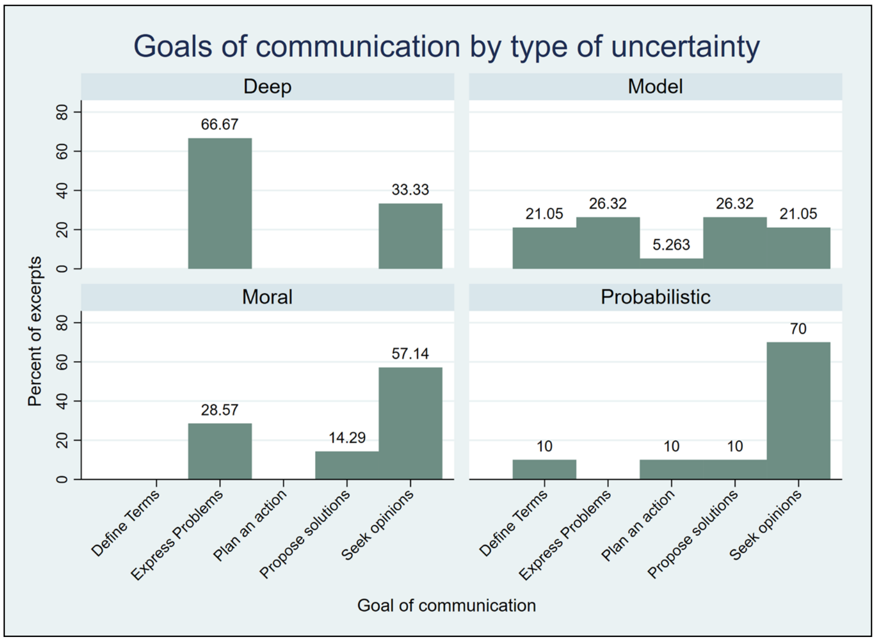

Figure 4 Goal by Uncertainty Type

Expressing uncertainty when seeking solutions and opinions from stakeholders and the public runs counter to scholars arguing for a rigid and "iron-triangle" structure between agencies, stakeholders, and political authorities (McCubbins, Noll, and Weingast 1987; McGarity 1996). However, this limited analysis does not tell us whether the comments are indeed incorporated, and more importantly, whose comments are heard most often. Several scholars have argued that industry stakeholders and interest groups representing them have a greater impact in the development of the rule, either because they get to participate early in rulemaking (Yackee 2012; C. Kerwin, Furlong, and West 2010; Golden 2003) or their comments after the proposed stage matter more to agencies (Yackee 2005; Naughton et al. 2009). This research does not delve into the influence of specific participants in the rulemaking of a given agency.

One other key finding is that 66.67% of the deep uncertainty excerpts had the key goal of expressing the problem. This is not surprising considering the difficulty of quantifying deep uncertainty.

Excerpts

Probabilistic (70%) and moral (57%) uncertainty dominated in the types of regulatory texts that sought public opinion and hence will be the focus of the following section. The following is an excerpt of probabilistic uncertainty due to data quality seeking public opinion through Q&A:

DOI: 10.21061/cc.v4i2.a.50

> Are there any barriers or challenges that data quality and data processing pose for developing, adopting, and managing AI? If so, please provide details on those barriers or challenges. Question 5: Are there specific uses of AI for which alternative data are particularly effective? (FDIC 2021, 16840)

Although limited by the number of excerpts to make broad generalizations, the contrast in different goals sought between probabilistic and moral uncertainty excerpts is an interesting finding. Moral uncertainty excerpts were usually followed by the expression of problems, and in the instances where public opinion and solutions were sought, they only involved broad ideas such as the value of assigning a person as a driver in an ADS. However, with probabilistic uncertainty as seen above, the excerpts were followed by specific questions on how to source data or methods. This could be a consequence of how excerpts have been categorized and coded but could also imply that agencies only consult the public on data requirements and merely acknowledge issues that raise ethical concerns.

DISCUSSION

The results show that uncertainty type plays a role in how uncertainty is communicated and for what purpose. Textual descriptions were found to be used extensively to describe the uncertainty inherent in nature, whereas numeric values were used in reference to human-designed models. One possible explanation could be the lack of proper quantification of uncertainty inherent in nature. This is consistent with scholarship indicating that this is an undetermined uncertainty (Der Kiureghian and Ditlevsen 2009). Another possible explanation is that model uncertainty stems from human-designed models and risk-averse agencies lean toward quantifying and estimating the degree of uncertainty (Jones 2007). This study highlighted overlapping and sometimes alternative means of addressing uncertainty. This study also found parallels with the sound science and evidence-based approach, where numbers and estimates are implicitly used to communicate model uncertainty, whereas explicit communication using text is seen frequently with all types of uncertainty. Such an explicit approach highlights a case where the acknowledgment of uncertainty might be used to seek consensus.

The results highlight two divergent goals in communications with the public: 1) to enhance existing knowledge/data, and 2) to resolve and develop consensus on value-judgment and accountability issues. Both cases are examples of the intention to engage with stakeholders and the public as a way to signal trust-building (IOM 2013; Kreps and Kriner 2020; Frewer and Salter 2010).

This also happens early in the decision-making process and is evidenced in this study as well. A majority (54%) of documents where uncertainty was expressed came from notices sent before proposed regulations were formulated. This is consistent with similar studies in the Canadian regulatory context where disclosure of uncertainties was uncommon and only seen in guidelines (Pavlyuk et al. 2017). The findings could mean one of many things for this research. One, this could be a strategic attempt by agencies to avoid challenges by any other branch of government or unsupportive interest groups, as some authors have suggested (Potter 2019; C. M. Kerwin and Furlong 2019). Another contributing factor could be that agencies are opting to circumvent the burdens associated with notice and comment rulemaking by relying on guidance documents and interpretive statements. While scholars have argued that these non-binding instruments are a coercive means to secure compliance, they may also serve as a way for agencies to navigate uncertainties and maintain flexibility in their regulatory approaches (Parrillo 2019; Mashaw and Harfst 1990).

Lastly, these findings could also point to the widening gap in the pace at which the development of certain technologies is accelerating and the inability of legislative and regulatory institutions to address them (Marchant 2011). This is more likely the scenario with emerging and unanticipated challenges with generative AI (e.g., ChatGPT) and Autonomous Vehicles (AV). Scholars have proposed alternative mechanisms to address regulatory challenges and build public trust while fostering consensus within regulated industries. These alternatives include business and self-regulation (Haufler 2013; Gunningham, Kagan, and Thornton 2004; Vogel 2008), involvement of third-party and community organizations (Gunningham and Sinclair 2017), and congressional oversight (McCubbins and Schwartz 1984). Each of these mechanisms carries distinct implications for promoting public trust and generating consensus within the regulated industry.

In summary, the use of text and narratives with the key intention of collecting stakeholder and public opinion predominated in agency communication of scientific uncertainty with AI regulations.

LIMITATIONS & OPPORTUNITIES FOR FUTURE RESEARCH

This study referenced a limited number of documents; hence, generalizations from such a small sample should not be made. Several additional factors could influence how agencies communicate uncertainty. Some of them include organizational factors like agency expertise and age; political factors, such as who was nominated to lead the agency by the executive and congressional branches; and the substance of the rule, such as its complexity and salience.

This study is also limited to regulatory texts and does not include public comments. Without analyzing the language of public comments and the changes made between the original and final regulatory text, it is not possible to claim whether the public opinion sought was utilized in resolving uncertainty. Regulatory agencies could respond differently based on their interpretations of commenters' understanding of different types of uncertainty. If commenters seem well-informed, the agencies might disclose uncertainties more frequently and over different areas. However, if the comments seem to be misinformed, agencies might be less willing to disclose uncertainty for fear of causing misunderstandings or panic. Future studies can incorporate these factors in their analytical approach, which could involve text-based natural-language processing, such as disclosures of uncertainty in regulatory texts (Pavlyuk et al. 2017) or statistical regressions to understand the influence of comments (Yackee 2005), politicking, and strategic rulemaking by federal agencies (Potter 2019).

DATA ACCESSIBILITY STATEMENTS

The data that support the findings of this study are available upon request to the author.

ADDITIONAL FILE

The additional file for this article can be found as follows:

- **Supplemental Appendix.** Tables A1-A3. DOI: https://doi.org/10.21061/cc.v4i2.a.50.s1

COMPETING INTERESTS

The author has no competing interests to declare.

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TO CITE THIS ARTICLE:
Phutane, Aditya Sai. 2023. "Communication of Uncertainty in AI Regulations." *Community Change* 4(2): 3. DOI: https://doi.org/10.21061/cc.v4i2.a.50

Submitted: 14 March 2023
Accepted: 06 July 2023
Published: 09 October 2023

Community Change is a peer-reviewed open access journal published by VT Publishing.

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