COGNITIVE AGENTS FOR WAYFINDING UNDER UNCERTAINTY IN UNFAMILIAR INDOOR ENVIRONMENTS

A Dissertation

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ABSTRACT

COGNITIVE AGENTS FOR WAYFINDING UNDER UNCERTAINTY IN UNFAMILIAR INDOOR ENVIRONMENTS

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Designers often want to understand how a building will perform before it is constructed. However, feedback on human behavior and experience is often unavailable during the early stages of architectural design, despite existing research in environmental psychology and post-occupancy evaluation. This dissertation addresses this gap by developing a cognitive agent, an evidence-based computational model of human behavior that offers designers meaningful human feedback. The research focuses on the problem of wayfinding in unfamiliar indoor environments, a widespread challenge in architecture that can lead to wasted time, increased costs, and user anxiety. Central to this investigation is the concept of perceived uncertainty, a critical factor influencing human navigation. The dissertation presents one scoping review, two empirical studies and two modeling studies. The empirical studies introduce a continuous measure of perceived uncertainty and highlight the importance of the rhythm of information acquisition in shaping navigation behavior and experience. These studies also generate rich datasets that support the development and validation of computational models. The scoping review identifies methods and opportunities for modeling human behavior in unfamiliar spaces. Two agent-based models are proposed. The first relies on rule-based heuristics and data-driven predictions of perceived uncertainty. The second is grounded in utility and information theory. The latter model, called PATH U.2, shows strong alignment with human participants by accurately reproducing route choices and the diversity of navigational paths. Together, this work advances understanding of the human wayfinding process in unfamiliar environments and introduces computational models that represent this process in a concise and interpretable form. These models offer new tools to support designers in creating environments that better respond to human needs and behaviors.

Biographical Sketch

Qi Yang is an interdisciplinary researcher with a background in architectural design, environmental psychology, and systems engineering. Qi’s research centers on understanding the complex processes of human-building interaction through a research-through-design approach. Qi asks: How can we envision novel design tools that support more evidence-based and creative design processes?

In addition to empirical investigations and predictive models of human wayfinding behavior, as detailed in this dissertation, Qi integrates artificial intelligence and brain-computer interface technologies to develop human–AI co-creative tools. These tools aim to augment designers’ cognition and perception, ultimately supporting more informed and creative decision-making.

Prior to pursuing his Ph.D. at Cornell University, Qi studied architectural design at the University of Hong Kong (B.A. in Architectural Studies) and Columbia University (Master of Architecture). He has worked at several international architecture firms, where he led data-driven programming and community-centered participatory projects in rural China.

Acknowledgement

Pursuing a PhD is a wayfinding process filled with uncertainty, frustration, and anxiety. Yet it is also a journey rich with curiosity, joy, fulfillment, and moments of insight. Along the way, I hit dead ends, overthought decisions at intersections, felt exhausted in the middle of long corridors, and backtracked from many challenging yet promising directions. Still, I am grateful for the many side routes I explored and the moments when I allowed myself to be just distracted enough. As long as I follow my heart, it feels as though all these paths eventually converge at the same destination. Finishing a PhD is not the end, but rather a beginning.

As a designer without formal research training before starting my PhD, I cannot express enough appreciation for the patience, guidance, and support I received from my chair, Saleh Kalantari, and my wonderful committee members, Patrick Reed and Adam Anderson. They always showed up at the intersections where I most needed direction. I would also like to thank Nancy Wells, Gary Evans, Mardelle Shepley, Keith Green, and Renata Marques Leitao for their insightful feedback throughout my research journey.

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I would like to thank Jesus Cruz Garza, who supported my intellectual and technical development during my first year of the PhD. I also thank Rohit Dubey, who guided me when I was lost in the forest of computational modeling and simulation. And I thank Bill Xu, my colleague who introduced me to this PhD program and generously offered direct and critical feedback on research questions and statistics.

I am grateful for all the undergraduate and graduate research assistants I had the pleasure of working with. Your dedication and support significantly reduced the task completion time of my wayfinding.

Finally, thank you for finding and reading this dissertation. If you are also thinking about how we might understand human-building interaction and design a better environment for humans and other living beings, I believe we are searching for the same thing. High five.

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Chapter 1. Introduction

Imagine searching for the security checkpoint in an unfamiliar airport, locating a specific store in a vast shopping mall, navigating to the radiology department in a hospital, or finding a particular room in a newly designed office building. These scenarios become particularly stressful when time is limited, such as running late by ten minutes. Such tasks are known as wayfinding, which involves navigating physical environments, planning routes, and reaching desired destinations. Wayfinding is a critical part of daily life and failures of wayfinding can lead to anxiety, wasted time and resources, or even loss of life. In an era marked by rapid urbanization, increasingly complex buildings, and an aging population, effective wayfinding systems, which facilitate this process with minimal physical and mental effort, have become essential infrastructure.

1.1 Regular Wayfinding in Unfamiliar Indoor Environment

Human wayfinding behaviors vary significantly by context, necessitating different conceptual frameworks. One widely recognized framework categorizes wayfinding based on the availability of spatial knowledge and guidance [1]. However, this framework is not strictly adhered to in wayfinding research. A common distinction is between emergent and non-emergent scenarios. In emergent scenarios, such as evacuations, wayfinders are typically assumed to share a relatively uniform stressful mental state, with success measured by clear metrics like evacuation time. These studies often emphasize crowd interactions, assuming visual access to directional signs. In contrast, non-emergent scenarios focus more on individual decision-making. Another key distinction lies between indoor and outdoor/pedestrian wayfinding. Outdoor wayfinding is characterized by longer travel distances and reliance on global landmarks, while indoor wayfinding involves navigating intricate floor plans and complex environmental factors.

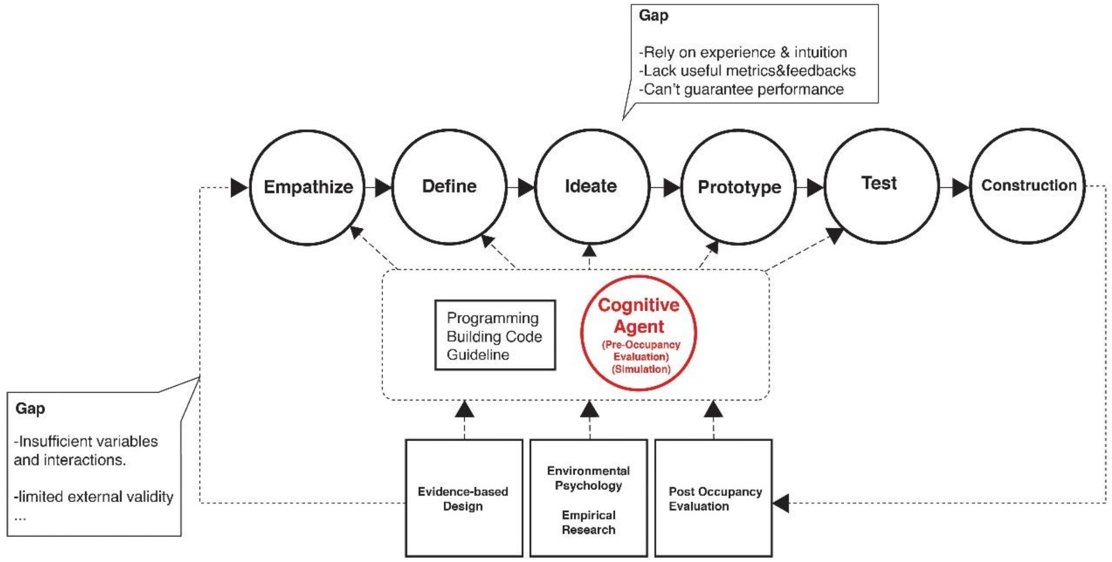
Although evacuation wayfinding has been extensively studied and modeled, research on non-emergent wayfinding in unfamiliar indoor environments remains very limited. This gap is notable, given that first-time visits to buildings are a frequent and significant wayfinding challenge for many people.

An integral experience during first-time indoor wayfinding in unfamiliar environments is *perceived uncertainty*: the metacognitive thought, "Am I on the right track?" This sense of uncertainty permeates the wayfinding process, manifesting in scenarios such as encountering intersections without signage, doubting floor levels, or misinterpreting room numbering systems. Perceived uncertainty drives various emotions and behaviors, ranging from curiosity to anxiety. In curiosity-driven states, individuals explore routes with a sense of possibility; in anxiety-driven states, individuals exercise caution, backtrack, and become more risk-averse. Despite its prevalence, little empirical research or theoretical work has systematically examined what triggers perceived uncertainty and how it influences psychological states and wayfinding strategies.

1.2 The Gap Between Empirical Studies and Design Practice

For designers of wayfinding systems, understanding the interplay between perceived uncertainty and human behaviors in unfamiliar environments is crucial. Predicting wayfinding

Figure 1 Fill the Gap Between Empirical Studies and Design Practice by Developing Cognitive Agent Models



challenges before construction remains a significant challenge due to the complexity of human-building interactions, variability in perception and decision-making, and the diverse strategies available for signage and spatial cues. Many designers rely on intuition and experience, which, while invaluable, are not transparent, easily transferable or scalable. Existing evidence-based wayfinding guidelines provide helpful heuristics but face limitations: they may be overly specific and prescriptive, limiting innovation, or too generic, offering little actionable insight. Wayfinding design, as a "wicked problem," requires a feedback system that is transparent, accumulative, adaptable, and accessible to support iterative design and innovative solutions (Figure 1).

A promising alternative to traditional guidelines is the use of computational models to simulate human wayfinding behaviors. Such models offer a dynamic and comprehensive hypothesis of how humans interact with environments, allowing for scenario exploration with individual differences, and robustness analysis. By leveraging computational models, designers can identify problematic areas, understand behavioral patterns, and either refine existing designs or innovate beyond the current paradigm. These models can also guide empirical research, enabling researchers to validate novel hypotheses and iteratively improve existing modeling frameworks. Recent advances in data-driven modeling, incorporating real-world data and machine learning, further enhance the accuracy and applicability of simulation results.

1.3 Research Goals

The ultimate objective of this dissertation is to develop a cognitive model of human wayfinding in unfamiliar environments, with a particular focus on quantifying experiential metrics such as perceived uncertainty and uncertainty-driven behaviors. This is an ambitious goal, given the limited understanding of how uncertainty is experienced during wayfinding and the scarcity of existing models that address unfamiliar navigation contexts. To pursue this objective, I structure the dissertation around the following guiding questions:

- What are the patterns and dynamics of spatio-temporal perceived uncertainty in indoor wayfinding?
- What factors influence perceived uncertainty, and how does it shape human wayfinding behaviors?
- What computational models are best suited for formalizing human wayfinding behaviors in unfamiliar environments with perceived uncertainty?
- What design insights can be derived from human behavior models?

1.4 Dissertation Overview

The dissertation is structured as follows. Chapter 2 introduces the theories and methods underpinning this work. Chapter 3 presents a scoping review of existing human wayfinding models, highlighting gaps and opportunities for improvement. Chapters 4 and 6 detail two empirical studies on perceived uncertainty. The first study develops and validates a tool to measure continuous and spatiotemporal uncertainty experiences, offering insights into factors that affect perceived uncertainty, while the second, conducted in virtual reality, provides further validation. Chapters 5 and 7 introduce two computational models, PATH-U and PATH-U.2, which explore different modeling frameworks, with PATH-U.2 offering enhanced scalability and accessibility. Finally, the dissertation contributes to future research by (1) developing a validated tool for measuring human uncertainty experiences, (2) investigating environmental factors influencing perceived uncertainty and its dual effects on wayfinding experiences and behaviors, and (3) proposing and validating two data-driven computational frameworks for modeling human wayfinding in unfamiliar environments.

Chapter 2. Uncertainty: Psychological Foundations and Computational Models

Uncertainty is a multifaceted concept with rich implications in both psychological and computational domains. This chapter provides a multidisciplinary overview of uncertainty and establishes the theoretical foundation for subsequent studies.

2.1 Uncertainty as a Psychological Construct

Uncertainty has been defined in various ways. One early definition characterizes uncertainty as "a state of an organism that lacks information about whether, where, when, how, or why an event has occurred or will occur" [2]. Similarly, Carleton describes uncertainty as the subjective experience of lacking knowledge, which may manifest at any level of consciousness [3]. Hirsh and colleagues integrated Shannon entropy into psychology, defining uncertainty as "a result of any experience that alters the shape of these probability distributions." [4], This perspective, adopted by Jonietz and Kiefer in their study of wayfinding uncertainty, highlights that uncertainty arises from conflicting information that challenges existing beliefs [5]. Maximum uncertainty or entropy occurs when a person perceives all potential outcomes as equally probable. Hirsh et al. also identified two key scenarios where uncertainty emerges: perceptual uncertainty ("What do I see?") and behavioral uncertainty ("What should I do?") [4].

Building on this, Bach and colleagues introduced first-order uncertainty, which describes situations where the probabilities of outcomes are known, and second-order uncertainty, or ambiguity, where these probabilities are unknown. [6]. Further, they proposed a comprehensive framework of four cognitive processes in which uncertainty can arise: (1) sensory processing, (2) state evaluation, (3) rule identification, and (4) outcome prediction [7]. This framework provides a structured approach to analyzing uncertainty at various cognitive stages. For instance, during the wayfinding process, a person encountering a worn-off sign may experience sensory uncertainty, questioning, "Is it room 101 or room 701?" This reflects uncertainty stemming from noisy sensory input. Upon resolving this ambiguity and deciding that the destination is room 101, the individual enters the second stage, state evaluation, answering the question, "Where am I right now?" If the person confidently identifies the location as the ground floor but encounters an elevator with confusing labels such as "2L," "1L," "T," "G," and "1," uncertainty shifts to the rule identification phase: "Which button will take me to the correct floor?" Later, after reaching the correct floor but finding two identical-looking corridors, the uncertainty evolves into the outcome prediction phase as the individual estimates the probability of each choice leading to the destination.

2.1.1 Uncertainty in Psychological Theories

Bayesian Brain Hypothesis. The Bayesian Brain Hypothesis suggests that the brain represents sensory data not as individual values but as probability distributions. This approach enables more effective processing of uncertain sensory information and facilitates the formation of judgments about the world. The hypothesis is closely linked to the concept of a predictive brain, which posits that the brain continuously generates and updates predictions about incoming sensory inputs based on prior experiences. In essence, the brain functions as a prediction machine, striving to minimize the discrepancy between its predictions and the actual sensory data it perceives [8].

Free Energy Principle. The Free Energy Principle provides a framework for understanding brain function by proposing that the brain, or any self-organizing system in equilibrium, aims to minimize free energy. Free energy refers to a measure of "surprise" or prediction error—the discrepancy between the brain's internal assumptions about sensory inputs and the actual sensory data received [9]. This principle underpins a wide range of theories about how the brain processes uncertainty and maintains equilibrium.

Approach Avoidance Theory. The Approach-Avoidance Theory, introduced by psychologist Kurt Lewin, highlights the dual processes of desiring positive outcomes (approach) while avoiding negative outcomes (avoidance). This framework accounts for the internal conflict individuals experience when faced with situations that have both attractive and adverse aspects. For example, one might want to eat dessert while worrying about its caloric content. The theory also introduces the concept of the "avoidance gradient," which suggests that as an individual approaches a goal with both positive and negative aspects, the avoidance tendencies often become stronger. This intensification can result in increased anxiety or hesitation [10]. The framework is extended to decision science, where researchers have identified differing tendencies in decision-making: some individuals exhibit uncertainty-seeking behavior, while others are uncertainty-averse. [11].

Exploration-Exploitation. Originally formulated in the context of reinforcement learning and the "multi-armed bandit problem," the Exploration-Exploitation Dilemma has since been applied to psychological phenomena. Exploration involves seeking new information, testing unfamiliar strategies, and expanding the range of potential options. In contrast, exploitation focuses on leveraging existing knowledge to maximize immediate rewards. Balancing these two processes is critical for achieving optimal decision-making outcomes [12].

2.1.2 The Dual Effects of Uncertainty on Anxiety and Curiosity

A substantial body of psychological research highlights the emotional effects of uncertainty, particularly its capacity to evoke anxiety and fear [3]. The Behavioral Inhibition System (BIS) plays a critical role in determining whether uncertain stimuli are perceived as threats. The BIS, a neuropsychological system designed to assess risks and inhibit potentially harmful behaviors, initially treats uncertainty as a potential threat. However, in a typical BIS, if no adverse evidence reinforces the threat, the system neutralizes the stimulus, leading to habituation [13].

The Uncertainty and Anticipation Model of Anxiety (UAMA) defines anxiety as "the suite of anticipatory, affective, cognitive, and behavioral changes in response to uncertainty about potential future threats" [14]. Anxiety, within appropriate levels, serves as an adaptive mechanism to avoid future threats. However, excessive anxiety, particularly in the absence of real threats, becomes maladaptive [15]. The UAMA model identifies five maladaptive responses to uncertainty in anxious individuals: (1) inflated threat estimates, (2) deficient safety learning, (3) heightened vigilance, (4) avoidance behaviors, and (5) heightened reactivity to uncertainty. Anxiety can develop through direct learning (e.g., personal trauma), vicarious learning (e.g., observing others), or instructional learning (e.g., being told to fear certain situations) [16]. For example, repeated failures in navigation, such as missing flights due to confusion at airports, can result in airport-related anxiety.

In addition to anxiety, uncertainty also elicits "fear of the unknown," a construct distinct from anxiety. While anxiety concerns the future consequences of uncertainty, fear describes immediate physiological responses to current threats. Evidence suggests that individuals with higher sensitivity to uncertainty, such as those prone to anxiety or depression, are more likely to develop a fear of the unknown [3]. Individual factors, including intolerance of uncertainty, genetic predispositions, and past experiences, influence the intensity of anxiety and its potential maladaptive consequences. Although evidence is insufficient to conclude that chronic exposure to uncertainty causes severe effects in healthy individuals, prolonged anxious patterns is a neurological practice and may strengthen associated neural pathways, leading to long-term negative impacts [3,14].

Spatial navigation often involves uncertainty that triggers anxiety, particularly when unsuccessful wayfinding leads to tangible losses, such as time or money. For example, visitors lost in transportation hubs may experience heightened stress, while disruptions caused by lost individuals in healthcare facilities can impact operations [17]. Physical environments should aim to minimize unnecessary stress and promote feelings of security, particularly for individuals more prone to anxiety.

Uncertainty also has a positive dimension, driving curiosity and exploration [18]. Curiosity, defined as an internally motivated form of information-seeking, rewards the brain even in the absence of immediate practical value [19]. Berlyne identified two dimensions of curiosity: perceptual curiosity, driven by novel stimuli, and epistemic curiosity, motivated by a desire to acquire knowledge [20]. For example, in a beautiful museum, individuals may initially explore novel architectural features and later seek out information about specific exhibits.

Gruber and Ranganath's PACE framework (Prediction, Appraisal, Curiosity, and Exploration) describes curiosity as a response to prediction errors in the brain. When sensory input deviates from predictions, the brain appraises the discrepancy, potentially triggering curiosity or anxiety. If curiosity is stimulated, it activates dopaminergic pathways and enhances memory encoding, reinforcing learning during exploration [21]. However, Hillen et al. observed that uncertainty's effects depend on the context, balancing its potential to foster curiosity against its capacity to cause anxiety and avoidance. [22]

Uncertainty's dual nature raises critical questions, such as under what conditions uncertainty becomes beneficial. Studies show that moderate levels of uncertainty enhance engagement and motivation, as seen in infants’ attention patterns, trivia-related curiosity, and the "Zone of Proximal Development" in education [23–25]. However, excessive uncertainty can lead to avoidance, as illustrated by individuals choosing not to learn about potential health risks [26]. These findings highlight the need for balance, ensuring that uncertainty stimulates exploration without overwhelming individuals.

In conclusion, while uncertainty can lead to anxiety and avoidance, it also has the potential to foster curiosity, exploration, and learning. Understanding the interplay between these effects is crucial for optimizing environments, such as architectural spaces, to balance uncertainty’s positive and negative outcomes.

2.1.3 The Neurological System of Uncertainty Processing

Given our discussion thus far, it's evident that the processing of uncertain stimuli activates intricate neurological pathways tied to prediction (i.e., posterior cingulate cortex), appraisal (i.e., anterior cingulate cortex), threat detection (i.e., amygdala), reward processing (i.e., striatum), emotional regulation (i.e., insula), decision-making (i.e., orbitofrontal cortex), and memory (i.e., hippocampus). While there isn't a definitive theory explaining the interplay between these pathways, Bach and Dolan's comprehensive review does shed light on how uncertainty at various processing stages (sensory, state, rule, and outcome) is encoded in the brain [7]. Their review introduced a taxonomy for uncertainty (discussed in section 1.2) and organized existing studies according to this framework. Their findings suggest that the orbitofrontal cortex (OFC), lateral intraparietal cortex (LIP), intraparietal sulcus, middle temporal visual cortex, frontal eye field, middle frontal gyrus, anterior cingulate cortex (ACC), supplementary motor areas, and anterior insula are correlated with sensory uncertainty.

As for state uncertainty, the review pointed to a study that revealed a correlation between BOLD response and the anterior prefrontal cortex, superior frontal gyrus, and Brodmann areas 9 and 10. However, the authors found no neuroimaging studies using uncertain rules as stimuli.

On the topic of outcome uncertainty, while many studies have been conducted, drawing a solid conclusion proves challenging due to the variety of distinct brain regions found to represent outcome uncertainty in different tasks. As the authors suggest, this could be due to outcome uncertainty not being a unitary construct, with corresponding brain regions depending on further clarification of context.

In relation to the curiosity pathway, the PACE framework suggests that the hippocampus and the anterior cingulate cortex initially detect context-based prediction errors. The framework then proposes that the appraisal process leading to curiosity takes place in the lateral prefrontal cortex, rather than in the anterior cingulate cortex, which is thought to inhibit exploratory behaviors due to anxiety. If curiosity is indeed triggered, the midbrain activates a dopaminergic neuromodulation process, which subsequently enhances memory encoding in the hippocampus.

In conclusion, my aim was not to provide a comprehensive overview of the neural systems underlying uncertainty, as that's beyond the scope of this dissertation. However, gaining some understanding of current theories explaining how uncertainty influences anxiety and curiosity in the brain remains beneficial.

Why is uncertainty relevant to navigation in architecture? A policy maker or designer might pose the question: should we strive to eliminate as much uncertainty as possible during wayfinding? As previously discussed, the answer relies on the wayfinding context. In time-sensitive scenarios (such as transportation hubs), there's little room for uncertainty. However, most wayfinding processes are longitudinal and should take long-term benefits into account. For example, in educational buildings where repeated visits are anticipated, the building's layout should aid occupants in developing a cognitive map. In settings like museums or shopping malls, uncertainty can encourage exploration and expose visitors to more exhibits. But an overload of uncertain experiences can lead to cognitive stress and avoidance behaviors.

The notion of completely eliminating uncertainty could result in overly simplified and monotonous spatial environments. Conversely, architects might create excessively complex spaces under the guise of introducing diversity, which can indeed cause unnecessary confusion for occupants. So, where lies the balance? This dilemma prompts me to explore the intricate relationship between an individual's perceived uncertainty and their navigational behaviors (search v.s. avoid), anxiety levels, and memory consolidation. My aim is to construct a predictive model that assists designers in their decision-making process and helps prevent potential missteps in the early stages of design.

2.2 From Theory to Models: Computational Representations of Uncertainty

Uncertainty, a ubiquitous phenomenon, arises from the need to describe unpredictable or ambiguous aspects of the world. In mathematical and engineering contexts, various frameworks effectively represent uncertainty, many of which are directly applicable to wayfinding modeling and simulations. Key approaches are outlined below.

Probability. Probability is one of the most fundamental and widely used mathematical frameworks for describing uncertainty. Intuitively, it quantifies the likelihood of an event's occurrence. For discrete random variables, a probability mass function (PMF) maps the prescribed possible outcomes to the interval [0, 1], where the sum of probabilities across all possible outcomes equals 1.

In wayfinding modeling, probability can capture the uncertainty of a wayfinder's choices at decision points, such as selecting a corridor at an intersection. A PMF might describe the probability distribution of a wayfinder choosing among three paths: $P(\text{Path A})=0.5$, $P(\text{Path B})=0.3$, and $P(\text{Path C})=0.2$. This probabilistic representation is foundational for modeling decision-making under uncertainty.

Shannon Entropy. Originating from information theory, Shannon entropy provides a measure of the uncertainty or randomness inherent in a variable's all possible outcomes. A higher entropy value indicates a greater degree of unpredictability, corresponding to higher information gain from new observations. Entropy theory has been adapted to the psychological field to describe the nature of uncertain experience [4].

Deep Uncertainty. Deep uncertainty refers to situations when decision parties can’t even define the “prior probability distribution for uncertain inputs to the system, the outcome of interest and their relative importance, and the system and its boundaries” [27]**.** Unlike conventional probabilistic approaches, modeling deep uncertainty requires tools like scenario analysis, robust decision-making frameworks, and exploratory modeling [28].

In the context of wayfinding, where a person serves as the decision-maker navigating an unfamiliar environment, deep uncertainty is pervasive and manifests in various ways. For instance, individuals often have imperfect perception, leading to uncertainty about whether they have accurately processed available information or fully recognized all route options at an intersection. In unfamiliar settings, wayfinders may lack clarity about what lies ahead, such as the characteristics of the next intersection or the overall scale of the environment. Additionally, in such environments, individuals frequently encounter delays in receiving feedback or confirmatory rewards after selecting a route. This lack of immediate feedback can obscure the evaluation of their choices, further compounding the uncertainty of decision-making in these scenarios. A robust model of human wayfinding behavior in unfamiliar environments should account for these interactions with deep uncertainty and provide tools to explore and address such scenarios effectively.

Bayesian Probability. Bayesian theory offers a subjective interpretation of probability, viewing it as an iterative process that integrates prior beliefs with new evidence to update the likelihood of an event. This process is encapsulated by Bayes' theorem, where posterior probabilities are calculated as a function of prior probabilities and the likelihood of observed evidence. Bayesian approaches are widely accepted in psychology and inspire models such as the predictive brain hypothesis [8]. These methods are particularly relevant for wayfinding scenarios, where agents continuously update their mental maps based on environmental cues.

Fuzzy Set. Fuzzy set theory generalizes classical set theory by allowing partial membership of elements in sets. This is particularly useful for describing situations where categorical boundaries are not sharply defined. For instance, a room measuring 400 square feet might be classified as both "small" and "medium" with different degrees of membership in each category. This flexibility provides a more nuanced way to capture the inherent vagueness in categorical descriptions [29]. Fuzzy set theory is especially valuable in wayfinding when modeling ambiguous spatial features, such as corridors that may be perceived differently by individuals.

Dempster-Shafer Theory. The Dempster-Shafer Theory (DST) provides a framework for reasoning under uncertainty, particularly when information from multiple conflicting sources must be integrated. Unlike probability theory, which assigns probabilities to individual events, DST uses belief functions to assign degrees of belief (or "masses") to sets of hypotheses. The total mass is constrained to equal 1. DST introduces two key concepts: belief, representing the minimum level of support for a hypothesis, and plausibility, representing the maximum potential support. The gap between belief and plausibility reflects the degree of uncertainty. DST's ability to fuse conflicting information sources makes it highly relevant for modeling cognitive processes in wayfinding scenarios, where agents must reconcile contradictory inputs [30].

2.2.1 Tools for Modeling the Impact of Uncertainty

This section provides an overview of how uncertainty affects the behaviors of wayfinding agents, highlighting several interconnected subtopics. First, humans encounter uncertainty in environmental perception, memory, and cognitive states, which necessitates the use of appropriate modeling tools. Second, because humans do not possess complete knowledge of their surroundings, they continuously interact with and adapt to the environment—an ongoing process that modeling frameworks should capture. Third, during decision-making, psychological uncertainty functions as a latent cognitive state mediating between environmental factors and behavioral outcomes. Inferring this latent state can potentially enhance the realism and accuracy of behavior predictions. Fourth, humans exhibit distinct behavior patterns under different cognitive states, underscoring the need to represent uncertainty within these models. Finally, because uncertainty is intrinsic to human behavior models, it may require parameter calibration and systematic validation. Here, uncertainty refers not to psychological ambiguity but rather to mathematical stochastic properties, encompassing uncertain behavioral trajectories and parameter values. Identifying the most robust human behavioral models and evaluating their performance thus calls for specialized computational tools.

2.2.2 Model Frameworks

This section introduces computational frameworks relevant for modeling human wayfinding behaviors.

Agent-based Model. Agent-Based Modeling (ABM) provides a computational framework for simulating the actions, perceptions, and decisions of individual agents within an environment—an approach particularly well-suited for wayfinding research. Historically, many models relied on aggregate or equation-based methods, which struggle to capture individual heterogeneity [31], adaptive decision-making, and dynamic environmental interactions. By contrast, ABM represents each agent as a unique decision-maker, endowed with specific attributes such as spatial knowledge, behavioral rules, and learning strategies, thus highlighting the fine-grained cognitive processes that drive movement and path selection

In wayfinding simulations, this level of detail is crucial for understanding scenarios where agents operate under uncertainty or need to update their strategies based on changing conditions (e.g., encountering new corridors, temporary signage, or partial environmental knowledge). Rather than averaging behaviors across a population, ABM tracks how each agent's internal state (e.g., memory of previous routes, real-time feedback from the environment) influences decision-making over time. Such individualized modeling enables researchers to examine how small changes—like different signage placements or fluctuating lighting conditions—affect agents' navigation choices at the micro level.

Moreover, while ABMs are often employed to reveal emergent crowd behaviors, they are equally powerful for studying individual or small-scale wayfinding scenarios. By allowing researchers to manipulate agent rules and environmental parameters, ABM facilitates systematic "what-if" explorations of diverse factors that shape navigation outcomes. Consequently, ABMs are well-equipped to handle the complexity and variability that characterize real-world navigation, offering a robust tool for advancing both theoretical understanding and practical applications in wayfinding research.

Cellular Automata. Cellular Automata is another form of bottom-up modeling technique, and in many aspects, can be viewed as a special case of ABMs. Cellular Automata (CA) are discrete computational systems that track how local interactions within a grid of cells lead to larger-scale phenomena, an idea traceable to the work of John von Neumann [32].

Cellular Automata are defined by a few core elements that work together to produce complex dynamics from simple, localized rules. First, CA are typically laid out on a discrete grid, where each position—or cell—can be in one of a finite number of states (e.g., empty vs. occupied). Second, a neighborhood structure determines which cells influence a given cell's next state. Third, local update rules specify how a cell's state evolves at each time step based on its own state and the states of its neighbors. Together, these components form a flexible modeling approach that can potentially represent intricate human wayfinding behaviors.

Although commonly employed to explore crowd flow and emergent patterns [33], CA can also provide valuable insights into individual wayfinding in unfamiliar environments. Each cell in the grid updates its state based on locally applied rules—such as movement choices or perception of adjacent cells—and thus captures how an individual's incremental, context-specific decisions (e.g., deciding which adjacent cell to move into based on partial knowledge or environmental cues) accumulate into a coherent navigation path. This bottom-up approach affords computational efficiency and modeling flexibility, making it straightforward to incorporate factors like uncertainty, memory of prior locations, or reactive rule changes when encountering unexpected obstacles.

Finite State Machine. Finite State Machines (FSM) offer another perspective on modeling agent behavior that complements more general frameworks like ABM and CA. FSMs provide a systematic way to capture how an individual agent transitions between discrete states based on specific inputs or events. In essence, an FSM can serve as the internal "logic engine" governing an agent's behavior within an ABM, or it can structure how a cell in a CA updates its state according to contextual cues. Thus, FSMs often operate at a finer level of granularity, specifying when and why an agent (or cell) shifts from one behavioral mode to another.

Historically, Finite State Machines trace back to the seminal work of Edward F. Moore, who introduced foundational concepts for sequential machines [34]. A Finite State Machine (FSM) can be defined as a mathematical model consisting of a finite set of states, an initial state, the input, and well-defined transition rules that specify how the machine progresses from one state to another in response to inputs. This structure is especially valuable for computational modeling because it keeps the representation clear and tractable, especially useful in decision analysis where understanding transitions is a priority.

Similar modeling constructs exist that share the underlying principle of defining explicit rules or conditions for how an entity changes its behavior. Rule-based models, for instance, directly encode “if-then” statements [35]. Similarly, decision trees and behavioral trees [36] systematically branch out decision logic based on particular triggers or thresholds. Discrete event simulations revolve around discrete changes in a system at specific points in time, although they may not always adhere to the strict concept of states and transitions [37,38]. What unites these techniques is their reliance on discrete, condition-driven changes, making them useful for describing processes that can be broken down into distinct steps or phases during wayfinding.

In the context of wayfinding, Finite State Machines can characterize the sequence of actions and cognitive modes an individual might adopt when navigating unfamiliar settings. For example, an agent might begin in an “exploration” state, transition to a “decision-making” state upon encountering new signage, and, depending on external feedback, either move into a “backtracking” or “proceed” state. By structuring these states and transitions explicitly, researchers can capture how individuals handle uncertainty, update their cognitive maps, and react to environmental cues, all without losing the internal logic and clarity that FSMs provide.

Discrete Choice Model. The Discrete Choice Model (DCM) is a mathematical framework used to describe and predict individual decision-making among a finite set of alternatives. It was initially formalized by McFadden and has become a popular tool for modeling decision-making [39]. The model is based on the principle of utility maximization, wherein individuals are assumed to evaluate the utility of each available option and select the alternative that offers the highest perceived benefit.

A Discrete Choice Model typically consists of three essential components: (1) the set of alternatives, representing the finite options available for selection; (2) the utility function, which quantifies the attractiveness of each alternative based on observed and unobserved variables; and (3) the error term, capturing the stochastic elements of decision-making due to incomplete information or individual characteristics. The probability of choosing a particular alternative is derived by comparing the utilities of all available options [40,41].

Discrete Choice Models are relevant to modeling wayfinding in unfamiliar indoor environments, as they effectively represent decision-making under uncertainty. In such scenarios, individuals often face multiple choices, like selecting paths or directions at intersections. DCM can quantify the perceived utility of each option based on factors such as signage visibility, distance to the destination, and the presence of landmarks, enabling researchers to model and predict route choices [42].

Markov Decision Process. Markov Decision Process (MDP) is a mathematical framework to model sequential decision-making problems [43]. It consists of five components: (1) states (S) that represents different situations the agent can be, (2) actions (A) are the decisions agents can make, (3) transition probability matrix (Q) are the probability to certain state given the current state and action, (4) reward (R) function describes the reward received given the action in a certain state, and (5) policy (π) a function that returns an action given a state [44].

In wayfinding scenarios, MDP can encode decision points as states, potential movements as actions, and rewards based on factors like proximity to the destination, feedback from the environment and signs, or minimizing perceived uncertainty. Transition probabilities can account for uncertainties, such as misreading a sign or multiple interpretation of the environmental features. A well-designed reward function is crucial for successfully using this framework to model human-like wayfinding behavior.

It is important to note that training a typical MDP agent policy usually requires multiple epochs of exploration and reward-based learning. However, this classic iterative learning process is not essential when modeling the behavior of first-time visitors to a new building. The goal in this context is not to find an optimal wayfinding policy but to develop an agent that exhibits human-like navigation behavior. Nonetheless, MDPs can be used to model agents that dynamically update their policies as they gain familiarity with the environment, mimicking how humans develop cognitive maps through repeated exposure.

Imitation Learning. Imitation Learning (IL) is a machine learning approach where an agent learns to replicate the behavior of an expert by observing demonstrations, bypassing the need for explicit reward design [45]. Imitation learning complements the MDP framework by providing an alternative approach to policy learning. In this context, the agent's states, actions, and transitions are still defined as in a typical MDP, but the policy is derived directly from expert trajectories rather than a reward-driven optimization process.

Methods such as Behavioral cloning use supervised learning to map observed states to the expert's actions, effectively training the agent to imitate the demonstrated behavior. In wayfinding scenarios, instead of manually designing a reward function to reflect human preferences such as avoiding confusing paths, following signage, or prioritizing landmarks. IL can approximate these preferences by learning directly from recorded human navigation trajectories.

However, IL in wayfinding modeling faces key limitations, including its reliance on high-quality trajectory data and limited generalization. Small errors in actions can compound over time, further degrading performance [46]. Additionally, IL lacks mechanisms to adapt effectively to dynamic novel environments [47]. These challenges highlight the difficulties of applying IL to model human wayfinding, particularly when the objective is to provide designers with meaningful feedback on novel architectural designs.

Bayesian Network. A Bayesian Network (BN) is a probabilistic graphical model that represents the conditional dependencies among a set of random variables using a directed acyclic graph (DAG). Each node in the graph corresponds to a random variable, while the directed edges represent the probabilistic dependencies between these variables [48]. BN is a useful tool to reason under uncertainty with the ability to integrate prior knowledge with observed data for inference and decision-making.

The essential components of a Bayesian Network include nodes, edges, and conditional probability tables (CPTs). Nodes represent random variables, which can be discrete or continuous, while directed edges capture the relationships between these variables. The strength of these relationships is quantified in the CPTs, which specify the probability distribution of a variable given its parent nodes. Dynamic Bayesian Networks (DBNs) extend traditional Bayesian Networks by incorporating temporal relationships between variables, making them well-suited for modeling processes that evolve over time.

When applying to human wayfinding scenarios, which involves complex decision-making processes influenced by multiple interdependent factors, such as spatial knowledge, environmental cues, and cognitive states. BN provide a structured framework to capture these dependencies and represent the uncertainty inherent in human navigation. For example, a BN can model the likelihood of a wayfinder choosing a specific route based on visible landmarks, perceived distances, and prior navigation experiences.

However, like other data-driven models, Bayesian Networks (BNs) face limitations, including their reliance on high-quality data for accurate parameter estimation, difficulty in generalizing to novel datasets, sensitivity to prescribed model structures [49], and challenges in interpreting results of complex systems [50].

2.2.3 Parameter Estimation

To minimize the gap between simulated trajectories and human data requires optimizing the model parameters. As the parameter estimation problem in wayfinding involves a combination of non-linear interactions, stochastic influences, and high-dimensional data, it is inherently complex and computationally intensive. Compared with deterministic methods such as gradient-based optimization, stochastic optimization methods are more suitable because they can handle non-linear, discontinuous, and noisy objective functions while efficiently exploring the parameter space.

Genetic algorithms (GAs) are a robust choice for this type of optimization, as they are well-suited for complex, non-convex parameter spaces and do not require gradient information. GAs simulates an evolutionary process, where a population of parameter sets evolves through selection, crossover, and mutation to identify optimal configurations. The workflow begins with initializing a diverse population of parameter sets, which are evaluated using the simulation-based objective function. The most successful parameter sets, based on metrics such as similarities of trajectory and spatial uncertainty distributions are selected as parents. New offspring are generated through crossover and mutation, with occasional random perturbations to maintain diversity. This process repeats over multiple generations until convergence. The efficacy of GAs for high-dimensional, complex optimization problems has been well-documented [51].

Bayesian optimization (BO), in contrast, is particularly suitable for sample-efficient optimization of expensive-to-evaluate models. BO employs a probabilistic surrogate model, such as a Gaussian process, to approximate the objective function. It begins with an initial sampling of parameter configurations, followed by training the surrogate on the simulation outcomes. An acquisition function identifies the next parameter set to evaluate, balancing exploration and exploitation until the optimal set is found. This efficiency makes BO ideal for computationally intensive wayfinding simulations [52].

In selecting an optimization method for parameter estimation in wayfinding models, the rationale depends on several factors, including the complexity of the objective function, the dimensionality of the parameter space, and the computational cost of simulations. When the parameter space is high-dimensional and the optimization landscape is rugged or discontinuous, methods like genetic algorithms (GAs) are advantageous due to their ability to explore broadly and avoid getting trapped in local minima without requiring gradient information. On the other hand, when the simulations are computationally expensive and the parameter space is moderate in size, Bayesian optimization (BO) is more suitable because it balances exploration and exploitation efficiently through surrogate modeling, minimizing the number of function evaluations.

2.2.4 Model-based or Model-free Approach

Model-based and model-free approaches each offer distinct advantages and trade-offs for modeling wayfinding in unfamiliar environments. Model-based methods rely on a predefined structure, such as utility functions or cognitive frameworks, to simulate decision-making processes [53]. These approaches are interpretable and allow explicit integration of cognitive principles, like uncertainty-driven behaviors [54]. However, they can struggle with capturing unexpected or emergent behaviors due to their reliance on predefined assumptions. In contrast, model-free methods, such as machine learning methods, make fewer assumptions about decision-making processes and instead learn optimal behavior directly from data [55]. This flexibility allows them to adapt to complex, data-rich scenarios, but at the cost of high-quality dataset, reduced interpretability and potentially higher computational demands. In the context of wayfinding, the choice between these approaches depends on the research goals: model-based methods excel in providing theoretical insights and transparency, while model-free methods are better suited for exploring large, unstructured datasets or scenarios where human behavior is less predictable. A hybrid approach that combines the strengths of both methods may offer a promising direction [56].

2.2.5 Model Evaluation.

Evaluating the model enhances its transparency by helping users understand when we should and when should not use the model, and when it fails, what could be the possible reasons. Evaluation creates a healthy iterative evolving feedback loop. The evaluation usually includes verifying, validating, and testing [57]. Verification ensures conceptual model structure is correctly translated to computational methods. Validation ensures the model output resembles expected human data to a sasisfactory degrees. Testing includes broad testings for its generalizability, applicability, and acceptance.

Empirical Validation. Empirical validation is a critical step in ensuring the model aligns with observed human behavior. This process involves comparing model outputs, such as simulated wayfinding trajectories and decision-making patterns, to empirical human data. Human data can be collected through field studies or controlled experiments where participants navigate unfamiliar environments under varying conditions. Key metrics for comparison include trajectory similarity, route choice distributions, and perceived uncertainty alignment.

To evaluate the outcome of model under stochastic conditions, Monte Carlo Simulation provides a powerful tool. Monte Carlo simulations generate a wide range of potential outcomes by repeatedly sampling from the model's parameter space and stochastic elements. This technique helps quantify the variability in outputs, revealing whether the model consistently replicates observed behaviors or exhibits instabilities under different scenarios [58]. For example, by varying environmental layouts, cognitive state thresholds, or decision-making weights, Monte Carlo simulation can assess how closely simulated trajectories match human data distributions. Such simulations allow researchers to identify the probabilistic range of outcomes and detect any systematic biases or failure modes.

Scenario Testing. Beyond merely assessing the gap between model predictions and empirical data, the value of a model should be evaluated through other dimensions [59]. For example, models serve not only as predictive tools but also as instruments for posing critical questions and exploring scenarios that are impractical or impossible to test in real-world settings, thereby offering valuable insights to decision-makers [28]. Scenario testing, in particular, enables the evaluation of a model's adaptability and robustness under extreme or atypical conditions, such as environments lacking signage, highly ambiguous spatial layouts, or time-constrained navigation tasks. This process is essential for assessing the model's capacity to replicate human-like behaviors in novel or challenging contexts. By systematically varying inputs and environmental constraints, scenario testing facilitates the identification of potential failure modes and guides iterative refinements, ultimately enhancing the model's accuracy, reliability, and applicability.

Sensitivity Analysis. Establishing trust between the user and the model is essential, underscoring the importance of model transparency. Transparency refers to the clarity with which a model's structure, assumptions, and decision-making processes can be understood and scrutinized by users [60]. One critical method for enhancing transparency is sensitivity analysis, which evaluates how variations in model parameters influence outputs [61]. This analysis helps identify key parameters that significantly affect model predictions, such as weights assigned to spatial curiosity or thresholds governing uncertainty-driven behaviors. Furthermore, sensitivity analysis is instrumental in ensuring that model outputs remain stable under reasonable variations in input values, thereby highlighting parameters where the model may exhibit excessive sensitivity or, conversely, demonstrate robustness. This process not only improves model reliability but also fosters user confidence in the model's predictive capabilities.

Chapter 3. Modeling Human Wayfinding in Buildings: A Scoping Review

3.1 Abstract

Indoor wayfinding plays a vital role in everyday activities, and can become a matter of life-or-death in emergency situations. Simulation and modeling practices can help improve wayfinding designs prior to the construction or renovation of complex buildings. This scoping review synthesizes information from 50 recent studies to provide a summary of the state of the field in indoor wayfinding simulation. It investigates how researchers define wayfinding problems, the modeling methods, and the variables and data integrated into these simulations. It reveals critical gaps in research practices that hinder the full potential of wayfinding simulations. These include the sophistication of environment encoding, the types of wayfinding heuristics, and the limited implementation of perceptual, cognitive, and memory factors. The review also identifies a critical lack of large-scale empirical datasets for developing and validating human wayfinding models. It proposes future research directions to support more realistic models that enhance computer-aided design, decision-support systems, and ultimately enable automated building designs optimized for intuitive and efficient navigation.

Keywords: Indoor Wayfinding, Unfamiliar Environment, Modeling, Simulation

3.2 Introduction

Wayfinding, defined as the process of planning a route and reaching a desired destination [1], is a fundamental yet complex daily activity. Struggles with wayfinding in built environments can lead to a variety of negative outcomes, ranging from missed appointments, stress and anxiety, to potentially life-threatening consequences in emergency situations. Wayfinding difficulties often increase with age, making it particularly important to provide intuitive wayfinding systems for use by older adults [62,63]. First-time visitors to a building particularly face heightened wayfinding difficulties as they lack prior spatial knowledge of the environment [64].

However, designing for optimal wayfinding performance is challenging due to the inherent complexity of the wayfinding process, which involves continuous perception, cognition, and action under conditions of uncertainty [65]. Wayfinders must interpret spatial features, directional signs, landmarks, and memory cues, and all of these processes may be influenced by a building's social context as well as by the wayfinder's personal characteristics [65,66].

To better understand these uncertainties and improve wayfinding designs, researchers have developed computational models and ran simulations that predict potential wayfinding outcomes. These tools provide human feedback, thereby helping to evaluate new building designs and identify potential problems prior to construction [28]. Recent models integrate data from prior empirical studies [67,68], which can potentially lower the barrier to evidence-based design [69].

Wayfinding behavior modeling is a rapidly advancing field, and we need to understand how far we are from predicting realistic indoor human wayfinding behaviors in unfamiliar environments. To date, no scoping review has comprehensively examined such models. Previous reviews have focused on building occupant behavior models [70,71], building performance simulation [72,73], and general human-building interaction [74]. Some have addressed specific scenarios or techniques, such as pedestrian evacuation [75], cellular automata for crowd evacuation [33,76] and crowd simulation [77]. Nevertheless, a gap exists in synthesizing how current wayfinding modeling efforts inform future indoor wayfinding models for individuals without prior spatial knowledge. The only such review paper that we were able to find was outdated, addressing modeling efforts that mostly occurred before year 2000 [78]. Many new technologies and wayfinding-simulation endeavors have emerged over the past decades, creating a need for an updated synthesis and comparison.

In the current paper we provide such a review, focusing on the following questions:

RQ1: How do recent studies define the indoor wayfinding problem?

RQ2: What frameworks have been used to model spatial-temporal indoor wayfinding behaviors?

RQ3: How valid are existing wayfinding models in representing human behaviors?

By addressing these questions, we aim to offer a conceptual framework describing the state of the field and to suggest productive future directions for modeling indoor human wayfinding in unfamiliar environments. Ultimately such endeavors will contribute to the design of more user-friendly buildings.

3.3 Methods

We employed the PRISMA protocol [79] for the selection and screening of scientific articles to review. The following sub-sections explain this process and present our rationales and steps for information extraction.

3.3.1 Identification of Studies

Five major research databases were searched during the review: Web of Science, Scopus, IEEE Xplore, PsycINFO, and PubMed. To ensure inclusivity, we began with broad search terms, structuring our keywords around the intersection of three key categories: "continuous human experience and behaviors," "predictive models," and "spatial environment." Within each category, we incorporated synonyms, commonly used terms, and derivative forms to capture a comprehensive range of studies.

3.3.2 Screening

We extracted a total of 6122 articles from the databases, including 292 from Web of Science, 3975 from Scopus, 1835 from IEEE Xplore, 20 from PubMed, and 0 from PsychINFO. Out of this total, 452 duplicate items were removed. We then conducted an initial screening of the articles by title and keywords and excluded those whose keywords demonstrated a clear lack of relevance to human wayfinding behaviors (some examples of irrelevant keywords were "robot," "seismic," "power grid," "wind load," "thermal," "nuclear," "ventilation," and "water resources"). After this initial screening, 279 articles remained.

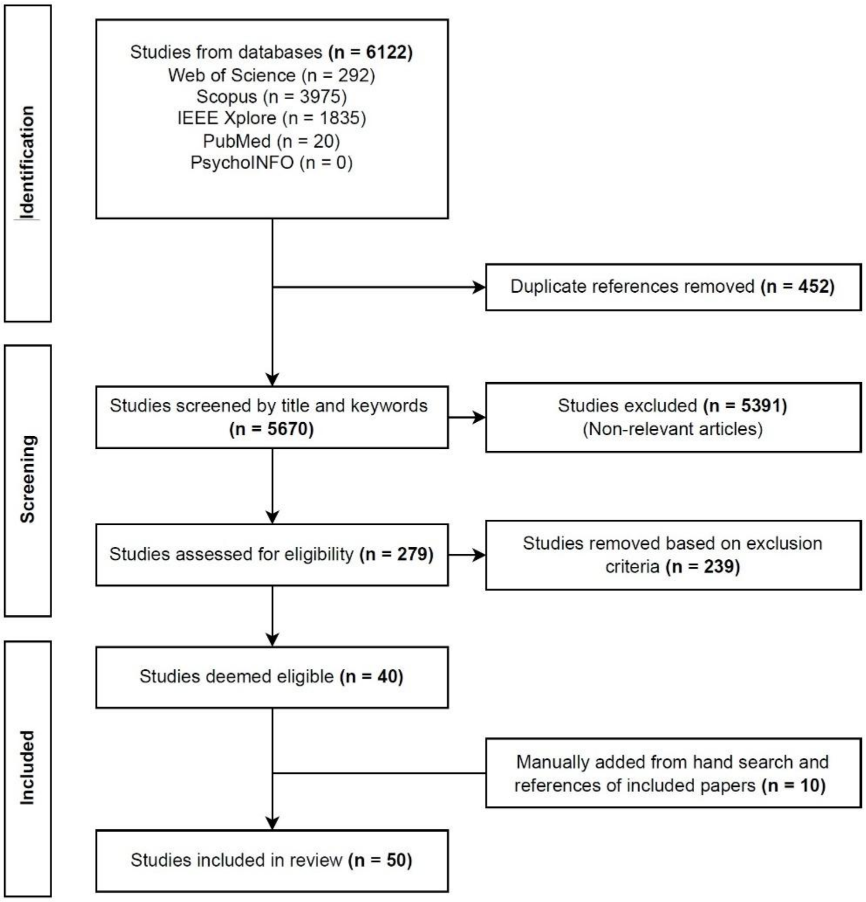
The next step was to conduct full-text screening of the articles based on our exclusion criteria. This process resulted in: (a) 28 articles removed because they were empirical research; (b) 9 articles removed because they applied existing off-the-shelf models to specific scenarios instead of developing new models; (c) 152 articles removed because they focused on performance optimization of existing models, behavioral recognition technologies, or broader simulation platforms not specific to wayfinding; (d) 6 articles removed because they were literature reviews; and (e) 44 articles removed because they focused on modeling only a single component of the wayfinding process (e.g., perception of signs) rather than the entire process of decision-making and behaviors to reach a destination.

These exclusions left us with 40 remaining articles. We identified 6 outdoor wayfinding studies. Though our study focuses on indoor wayfinding, we didn't exclude them because the outdoor environments in those studies are similar as indoor environments and their modeling approaches provide insights to indoor wayfinding. As a final step, we conducted a reverse search based on the reference lists of these articles, which resulted in identifying 10 additional studies that fit our criteria. Thus, we ended up with a total of 50 articles that were included in the review (Figure 2).

3.3.3 Information Extraction and Analysis

After reviewing the included papers, we developed a thematic framework to categorize the extracted information as relevant to our research questions. We identified how each included article addressed (or failed to address) the following topics: (a) framing the wayfinding problem, (b) overall modeling methods, (c) modeling the wayfinding environment, (d) modeling human perception, (e) modeling human cognition, (f) modeling human spatial knowledge (g) modeling human wayfinding strategies, and (h) model validation. This approach allowed us to obtain a structured overview of the methods that have been most commonly used in the field as well as their outcomes.

Figure 2 PRISMA Diagram of the Literature Selection and Screening



3.4 Results

The results of the scoping review are reported according to themes, with each theme linked to a corresponding research question.

3.4.1 Framing the Wayfinding Problem (RQ1)

While previous researchers have developed taxonomies of wayfinding problems [1], we observed that there was no consistent framing adopted in the included studies, and that they did not fit neatly into any pre-existing frameworks. The ways in which researchers understood wayfinding problems and outcomes were often quite different from each other based on the nature of their scenarios and their underlying assumptions. The scenarios in the included articles can be categorized along the following dimensions: (a) indoor vs. outdoor wayfinding, (b) emergency vs. non-emergency wayfinding, (c) room-scale vs. building-scale wayfinding, and (d) individual decision-making vs. crowd-level analysis. In addition to these dimensions, we identified several prevalent approaches to framing the wayfinding process: (a) shortest-path calculation, (b) discrete choice by time-step, and (c) dynamic and adaptive feedback loops.

In regard to their scenarios, the majority of the included studies (n = 43) examined indoor wayfinding, while 6 examined outdoor wayfinding and 1 examined both. Emergency wayfinding was addressed by 35 studies, while the other 15 examined regular (non-emergency) wayfinding. Building-scale decision-making was included in 33 studies, with 16 specifying room-scale wayfinding and 1 provides conceptual framework without specifying the environment. In regard to their scope of analysis, 19 studies focused on decision-making at the individual level, 20 studies focused on crowd interactions, and 11 studies included both. Overall, the main concern that emerges in regard to these diverse framings is that generalizations from one type of wayfinding study to another may not be warranted, increasing the difficulty of forming a comparative synthesis.

When it comes to understanding the wayfinding process, the first prominent approach is to simply use a **shortest-path calculation.** This framing is only viable in situations where sufficient knowledge of the environment and rational actions are assumed. It is most useful in scenarios such as crowd evacuation simulations, where the focus is on estimating the flow of traffic through multiple exits [80,81]. Additional applications may include the modeling of route utilization during long-term operations [82,83]; modeling emergent behaviors resulting from crowd interactions [84]; or itinerary planning [85], in which the goal is to determine an optimal sequence of destinations [86,87]. The shortest-path framing greatly simplifies the wayfinding modeling process and eliminates all uncertainty. Some nuance may be added through the incorporation of route weighting for different agents, to model factors such as individual proclivities and orientation [88]. However, this framing remains limited in its usefulness for reflecting nuanced real-world human behaviors in most wayfinding contexts.

The second main approach frames wayfinding as a **discrete choice process**, in which agents determine their movement direction at each of a series of time-steps. In this approach, the rationale for each decision remains consistent, but the choice is affected by the current environmental conditions. Thus, each discrete choice is treated independently from the other time-steps. Among other applications, this approach can be highly effective for room-scale evacuation scenarios, where the focus is on decisions among a limited set of exit options [68,89,90]. It enables modelers to account for more nuanced human actions, such as noticing that an exit is becoming clogged and therefore selecting a different route. The decision rationales used in the model can accommodate personal differences among agents, dynamic environmental features, and social interactions, effectively simulating complex, localized decision-making. However, this approach begins to diminish in utility in larger and more complicated environments, where human choices often take into account sequential experiences and iterative cognitive updates (for example, remembering that a previously attempted path was unsuccessful).

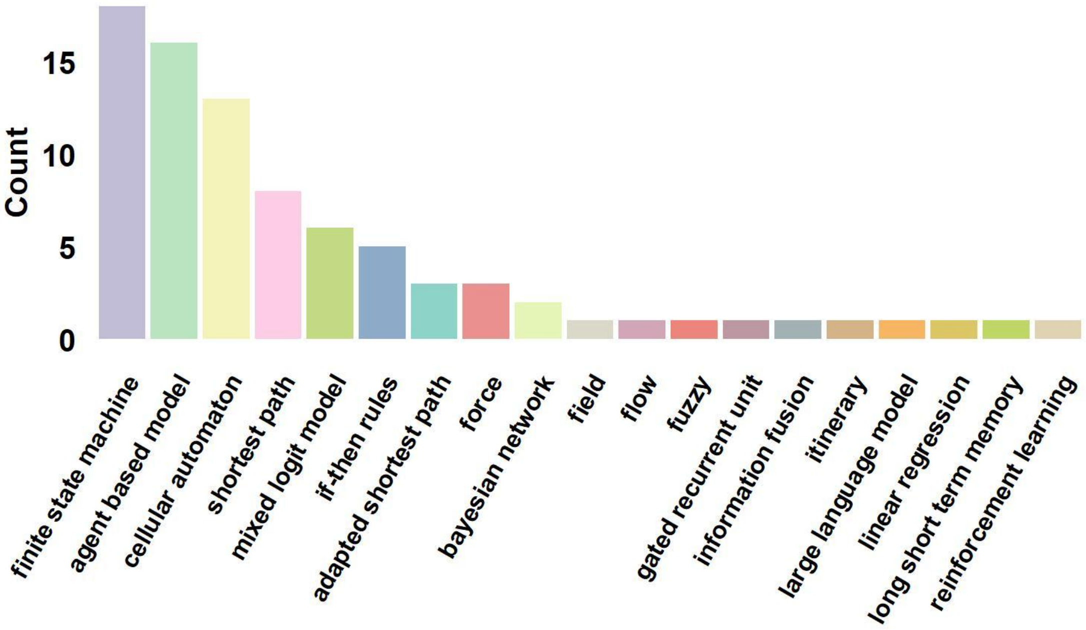
The third primary approach frames wayfinding as **dynamic and adaptive**, grounded in a continuous feedback loop of perception, cognition, and action [65]. In this approach agents adjust their decisions in response to their prior experiences as well as real-time environmental changes. Compared to the discrete choice framing, this approach enables much greater temporal and situational adaptability, enabling agents to iteratively refine their strategies through exploration or learning mechanisms [91–93]. However, it also greatly significantly increases the complexity of the modeling process, requiring higher computational demands and precise parameterization. Adaptive models are particularly suited to scenarios involving complex and continuous decision-making, such as building-scale and multi-stage wayfinding tasks.

3.4.2 Overall Modeling Methods (RQ2)

The most prevalent methods were finite state machines (FSMs), agent-based models (ABMs), and cellular automata (CAs). These approaches provide a good balance of accessible/intuitive design and adaptability to spatially complex environments. Shortest-path, mixed logit, and if-then methods saw a moderate usage; these approaches tend to be adopted for more simplified simulations. Force and flow models are similarly simplistic but are valued for their efficiency in crowd modeling. Figure 3 illustrates the types of simulation models that we identified in the included research literature (some studies used more than one type of model).

Some of the most recent studies leveraged advanced frameworks that may have a claim to heightened nuance in modeling human cognition. These include recurrent neural networks for trajectory prediction [94,95], reinforcement learning for modeling the effects of directional signs [96], Bayesian networks for cognitive-map updates [93], information fusion methods to model decision-making under conditions of conflicting information [30], and large language models applied to environmental reasoning and route planning [97].

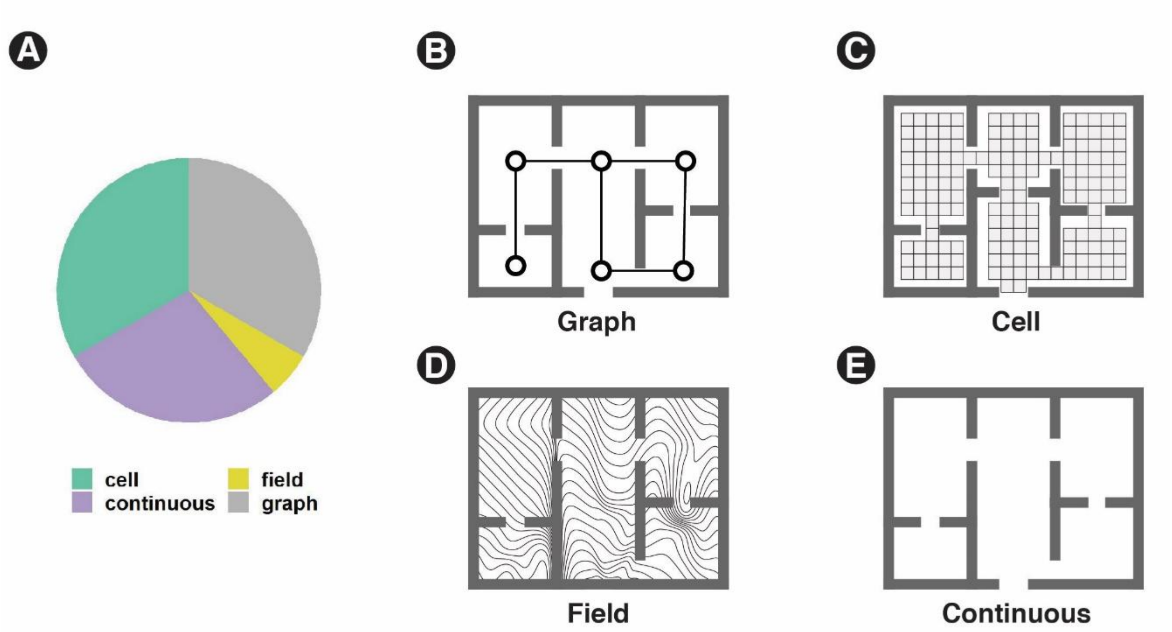
Figure 3 Distribution of Modeling Methods



3.4.3 Modeling the Wayfinding Environment (RQ2)

How indoor environment is represented can have a powerful effect on wayfinding simulations, particularly in the way that they model perception, planning, and action. The four primary approaches that we found in the literature were graph, cell, field, and continuous-plane models. (These are not entirely mutually exclusive; for example, a cell-based model used in cellular automata can also be interpreted as a specialized graph. For the sake of clarity, however, we will discuss each category separately.) Each of these four approaches has distinct strengths and limitations. Schematic examples are shown in Figure 4.

Figure 4 (a) Distribution of Different Methods for Modeling Wayfinding Environments, and Examples of: (b) Graph, (b) Cell, (c) Field, and (d) Continuous Plane.



Graph-based environments were used in 18 of the included studies. This approach represents relationships between spatial elements using “nodes” and “edges,” where the nodes typically correspond to rooms or intersections [98], and edges correspond to connecting paths or visibility between nodes [99]. This abstraction of spatial relationships is quite oversimplified, but it enables easy and concise quantitative analysis [100]. The wayfinding process is modeled as transitions between nodes, with possible edge weights reflecting path difficulty or other resistance factors [81,88].

One of the primary limitations of graph-based models is that they assume decision-making occurs only at nodes, and thus cannot be used to model on-route decision processes such as backtracking or gradual route adjustments in open spaces. They also tend to omit many vital aspects of spatial experience, such as the influence of size, color, form, or other environmental features, which can at best only be included by assigning edge-weights [68,101]. Similarly, associating the effects of directional signs with specific nodes can be difficult, since in some cases the signs may be located in the middle of a path rather than at an intersection. Translating large open spaces or complex corridors into graph representations poses a significant difficulty [102]. Graph-based environments are effective for simple layouts with clear decision points but may reduce simulation accuracy in complex environments due to the high abstraction.

Our review found that 18 of the included studies used **cell-based environments.** This approach models a grid-like matrix of spatial cells, defined as the smallest indivisible units with consistent properties [33]. This approach assumes wayfinders gain information only by moving to a different cell, as movement within the same cell provides no new information, effectively balancing the representation of spatial dimension and computational efficiency

The size of a cell can vary depending on the model's needs; for example, the two-dimensional measurement of 0.5m x 0.5m is common for pedestrian wayfinding [30,103]. Some models employ layered cell structures to accommodate different scales of information, such as overlaying smaller navigation cells with larger "zones" to model information congruence across larger areas [104]. Cell-based modeling is conceptually simple and easy to implement, while still supporting the simulation of fine-grained decision-making as well as complex crowd behaviors. This makes it suitable for a range of applications [103,105,106]. However, like the graph-based approach it is grounded in a fundamental abstraction of spatial relationships, which reduces the accuracy of simulations and can often result in unnaturally jagged movement patterns [107].

Among our included studies only 3 used **field-based environments.** This approach relies on scalar or vector fields that assign values to points in space [90,108]. Agents respond to these values by moving along gradients to minimize costs. Whereas graph and cell approaches prioritize discrete, local interactions between neighboring nodes/cells, field-based environments emphasize continuous spatial influences that guide movement in a gradated fashion. This has the strong advantage of enabling smooth and realistic navigation behaviors. Furthermore, by incorporating features such as perception masks or cognitive modifiers, field-based environments can readily account for memory, learning, and personal preferences, thereby enhancing the complexity and realism of simulated decision-making [90,97,104,109]. However, field methods do have some limitations, including a high difficulty of implementation and the need to translate discrete elements such as signs, landmarks, or obstacles into fields. Such models require meticulous calibration to ensure that different forms of spatial information are properly integrated and that the representation accurately reflects the modeled environment.

Finally, 16 studies in our review used **continuous-plane environments.** In this approach the space is modeled as a continuous domain, closely mirroring real-world contexts. The state of agents is represented via exact coordinates, facing direction, and velocity, allowing for smooth, realistic movement in any direction and at any speed [93]. This method provides high spatial-temporal resolution and precision, making it ideal for scenarios requiring detailed visual perception modeling [110]. The drawback is that dynamically modeling such spaces, which includes the integration of multiple information sources while determining agents' orientation and velocity, demands sophisticated algorithms and significant computational resources [40]. Many of the reviewed studies addressed this problem of resource-intensity by simplifying their modeling approaches, for example by using shortest-path algorithms in combination with continuous-plane environments. This approach may be viable for some scenarios, such as single-room crowd evacuation and occupancy modeling where route-knowledge can be assumed

[86,111]. Two of the reviewed studies were able to combine continuous plane environments with more sophisticated force models or recurrent neural networks to enhance the simulation of agent orientation and velocity [94,95].

3.4.4 Modeling Perception (RQ2)

The perception of an agent determines the information it can gather from the environment, which in turn influences cognition and decision-making. This sub-section highlights two approaches identified in the reviewed articles for modeling perception, described as (a) global and (b) local. We will also describe the different types of perceptual input variables that are commonly used in wayfinding models, drawing on a framework developed by Dubey et al. to categorize those variables [30].

The **global perception** approach simply assumes that agents have a perfect knowledge of all available information sources, and directly integrates this information into the cognition or decision-making process without considering uncertainty. For example, many cellular automata models for evacuation scenarios use the distance to each exit as a key input, and apply this information to route-planning without modeling how the agents might have learned it [81,106,112,113]. Some studies refine this method by introducing discounting parameters to account for imperfect perception, for example by applying a higher movement resistance value to paths that would be difficult for an agent to perceive [88]. Such indirect approaches generally require the researcher to make assumptions or suppositions about how the environment would be perceived and how it would affect agents' behaviors.

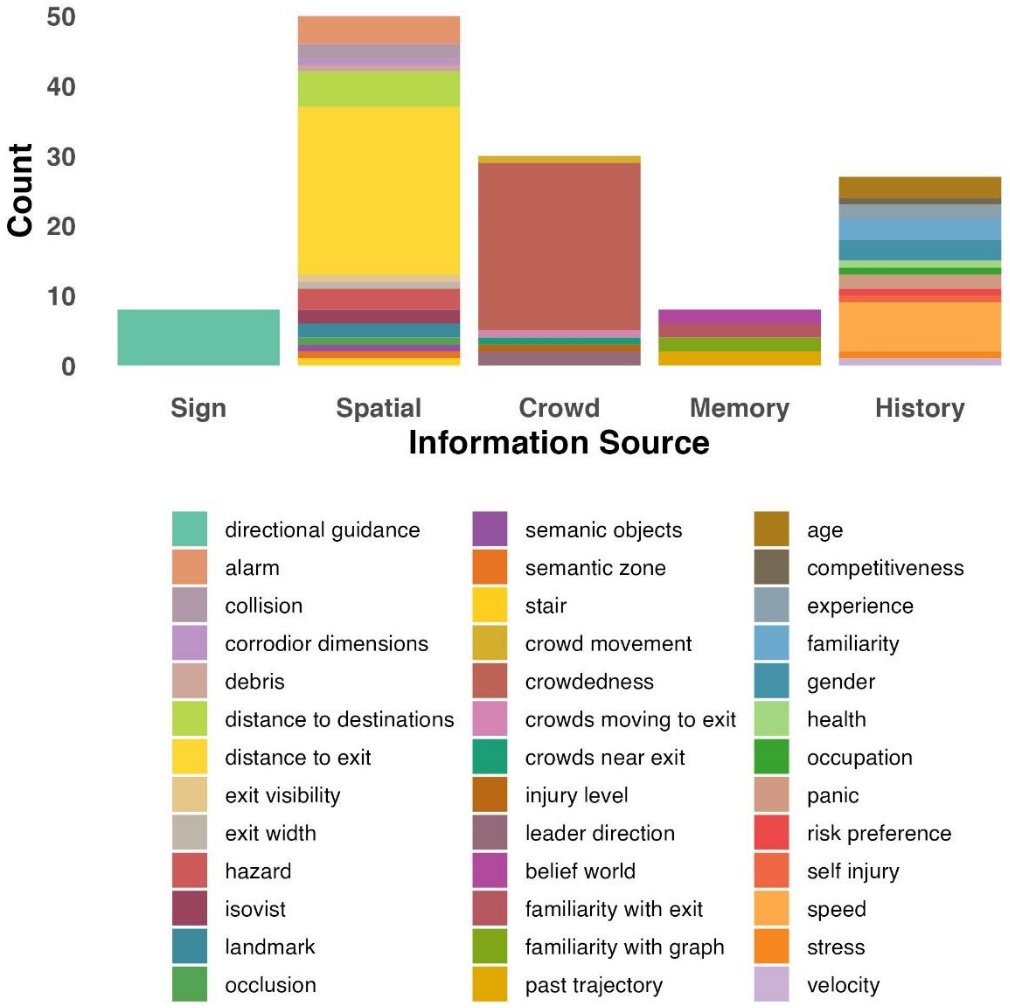
In contrast, **local perception** directly simulates human experience by modeling what an agent can perceive from its first-person perspective. This typically involves methods such as ray-casting or isovist calculations within a continuous field of view to detect objects [101,110]. Simpler proximity-based methods may approximate visual perception by defining a radius around the agent and considering anything within the radius as known [92]. While local perception approaches are unequivocally superior to global perception when it comes to capturing the nuances of human wayfinding experience, such models require dynamic evaluation as agents move through the environment, thus greatly increasing their complexity and computational demands.

Among the reviewed articles, 31 (62%) adopted the global perspective, and 19 (38%) adopted the local perspective. This ratio highlights the challenge of implementing a local perception model, making it less popular despite its advantages.

In regard to the types of perceptual input included in the models, we categorized this along five dimensions: directional signs, spatial features, crowd dynamics, memory, and history [30]. While not strictly perceptual in the standard meaning, “memory” and “history” are included here because they represent sources of information. “Memory” refers to prior spatial knowledge about the current environment, while “history” refers to assumptions, habits, typological familiarity, and personal preferences that the agent brings from their overall background. Salient “spatial features” includes items such as lighting, color, obstacles, and landmarks that may be relevant to selecting a route. More details about these categories are shown in Figure 5.

Many of the reviewed studies focused on a single type of perceptual variable, which can simplify models but overlook interactions with other variables. For example, in building-scale wayfinding, it was common for researchers to consider the perception of directional signs as the only source of wayfinding information [102,109]. Other studies focused solely on perceiving the distance to exits, especially in crowd evacuation scenarios [82,114,115]. The advantage of such approaches is that they enable researchers to delve deeper into nuanced aspects of specific perceptions and develop more realistic computational models of specific information sources. A study by Dubey and colleagues (2021), for example, investigated how viewing angles and distance affected sign perception, resulting in sophisticated models of this particular behavior [109]. Another study models landmark-based strategies, such as beaconing and reorientation, incorporating internal belief systems, perception uncertainty, and dynamic updates [93]. Other studies particularly examines spatial knowledge structures assimilated from crowd interactions [92,115]. In the context of crowd simulations, more detailed perceptual models could overcomplicate the model and influence behaviors of interest such as overtaking, following, and bottlenecks [84,116,117]

Figure 5 Variables Perceived by Wayfinding Agents in the Reviewed Studies



The selection of two or three information sources was also frequently seen in the reviewed studies. In evacuation scenarios, distance to exits and specific crowd properties (movement direction, emotions, injury level, etc.) were often used in combination [103,111]. Broader information sources, such as directional signs, tended to be viewed as irrelevant and omitted from these crisis-based simulations. Other researchers investigated agent behaviors influenced by signage and crowd movement, but without considering spatial features or memory

[30,118]. Some comprehensive frameworks integrated multiple information sources; for example, Pan ’s model analyzed information about signs, alarms, distance to exits, crowded density, memory, and individual differences [110]. Such expansive models are particularly well-suited to complex, building-scale wayfinding simulations, in which multiple sources of information are likely to be used during the completion of the wayfinding tasks.

When multiple sources of perceptual information are used, it becomes necessary to integrate them into a single decision-making model. Utility theory is a common approach for this; it requires the model to identify which information source provides the greatest utility for a particular wayfinding decision [68,119]. Some researchers use more simplistic rule-based decision trees (if-then rules)—for example, the decision model may first check to see if a sign is visible [118], then check to see if group leader is present [120], or check to see if an exit is familiar [110]. Another approach is based on the Dempster-Shafer theory, which uses belief functions to evaluate the agent’s confidence in different information sources [30].

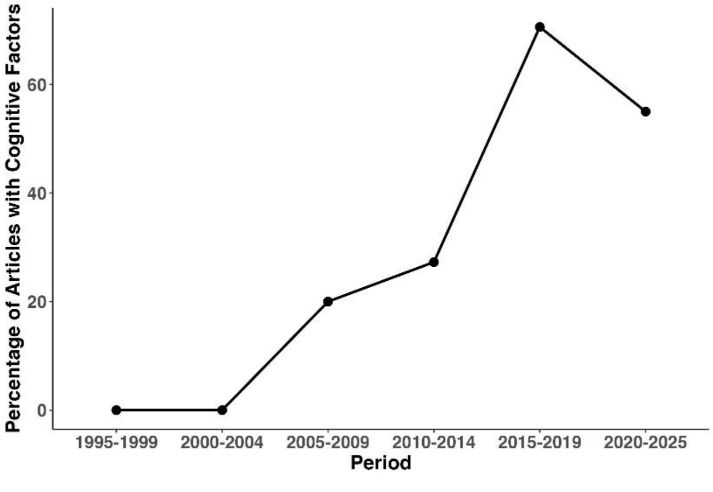
3.4.5 Modeling Cognition (RQ2)

Cognitive factors, such as confusion, stress, uncertainty, or confidence, were incorporated into wayfinding models in 30 (60%) of the reviewed articles. The remainder (40%) did not address any form of cognitive modeling. There was a noticeable chronological trend in this area, with more recent studies being more likely to integrate cognitive factors (Figure 6). Among the studies that took cognition into account, we identified two overarching approaches, which can be described as **static** parameters vs. **dynamic** variables. Static approaches were used in only 3 studies; for example, in the model created by Pan (2006) behavioral changes in simulated agents were triggered when their prescribed stress parameters exceeded certain thresholds. Most of the studies that integrated cognitive factors (26 out of 29) adopted dynamic models, in which cognition was evaluated on a continuum over time and had degrees of influence over agent behaviors.

The most common cognitive factors that were addressed in the reviewed studies were utility, panic, and stress. Agents' ability to evaluate route-choice utility was very frequently used to represent the extent of rational decision-making on the basis of available information [119]. Panic and stress, which are especially relevant in evacuation scenarios, were used to inform the modeling of behaviors such as irrational route choices and aggressive overtaking [103,111,121]. Additional cognitive responses, including uncertainty, confusion, disorientation, and familiarity, were addressed in some studies and modeled using techniques such as Gaussian noise [93], entropy-based formulations [109], rule-based systems [102], or prescribed values [99].

In general, we identified four basic modeling approaches for cognitive factors, including: (a) rule-based, (b) theory-driven, (c) linear combination, and (d) machine-learning. The rule-based approaches were associated with static modeling and relied on predefined conditions, such

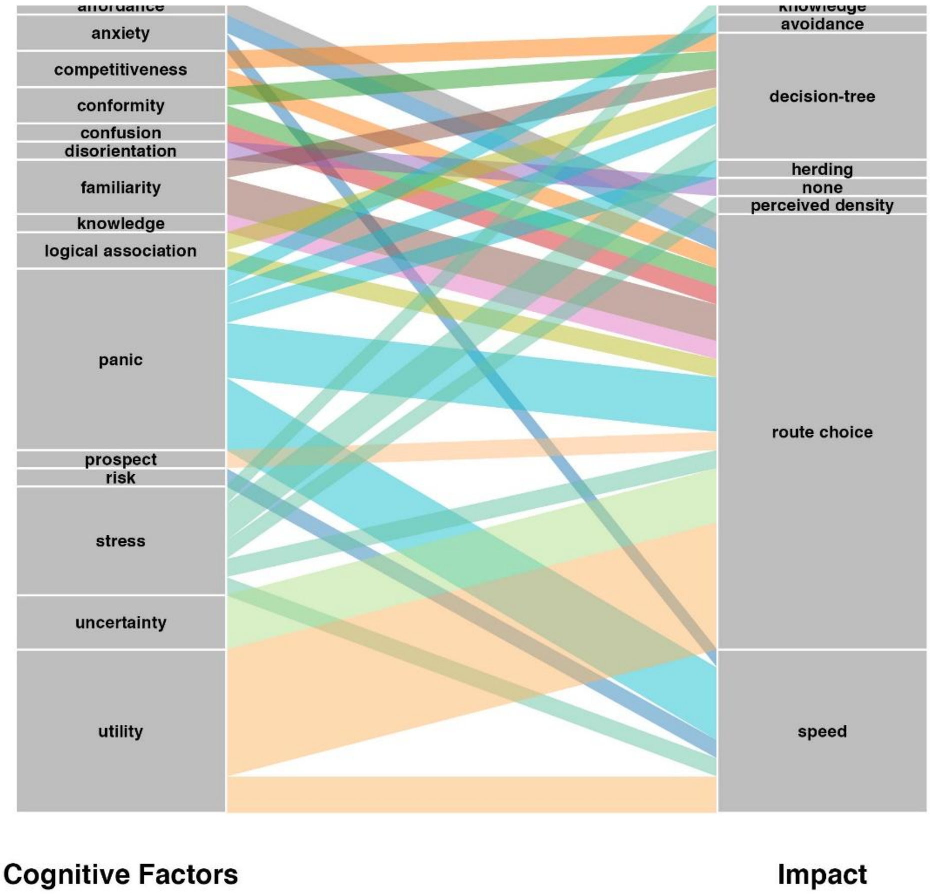
Figure 6 The Rising Chronological Trend of Incorporating Cognitive Factors into Wayfinding Models



as an agent entering a panic state when hazards and crowd density exceed certain thresholds [110,113]. While relatively easy to implement, such models are at risk of oversimplifying cognitive processes and their diverse behavioral outcomes. Theory-driven methods, such as entropy formulas or information fusion, require strong empirical validation in specific human populations. However, when appropriately used, they provide a solid and efficient foundation for modeling [4,109,119]. Linear combinations were the most frequently used approach in the reviewed literature; these models evaluate cognition as a weighted sum of influencing factors, offering flexibility and simplicity [111,119]. However, this approach assumes independence among factors and linear relationships, which may not always hold. Machine learning approaches, while capable of capturing complex, non-linear relationships, lack theoretical grounding and require large-scale, high-quality data [94,95].

Cognitive factors have been used to shape agents' decision-making in wayfinding simulations by affecting the clarity of agents' perceptions, the process of selecting exits, the evaluation of alternative routes, and other forms of behavior [90,106,122]. Additionally, they can be used to adjust agents' movement speed, which in turn affects crowd dynamics [105,119,123]. Researchers often use decision trees to capture how cognitive states drive varying behaviors; for example, in the model created by Tan and colleagues (2015), agents choose between the shortest route versus the most familiar route based on their stress levels [113]. De Iuliss and colleagues (2023) similarly used the level of panic to influence agents' likelihood of misjudging crowd density and random route choice [111] (Figure 7).

Figure 7 Modeling the Impact of Cognitive Factors during Wayfinding



3.4.6 Modeling Spatial Knowledge (RQ2)

Few wayfinding simulations modeled agents' spatial knowledge acquisition. It could be argued that all models based on recurrent neural networks inherently describe spatial knowledge, as they account for agents’ past trajectories; however, this seems at best a vastly oversimplified reflection of how humans come to understand their environments [94,95]. Tan and colleagues (2015) used a static model of spatial knowledge based on agents’ degree of awareness of exits, routes, and geometry, but this was treated as a fixed variable and the agents did not upgrade their knowledge during wayfinding [113]. G. J. Zhang and colleagues (2018) extended this approach by assigning to familiarity scores for specific sub-regions of the wayfinding environment, which could be updated over time as the agents moved through the areas [92]. These familiarity levels had an influence on the effectiveness of agents' route-selection in the model.

Rohit et al. advances this concept by automatically generating hierarchical representations through exploration. It incorporates sequential order effects, enabling agents to construct different spatial knowledge based on the exploration sequence. When planning, the agent uses Fine-to-Coarse wayfinding heuristics, mimicking human memory distortions [91]. Kessler and colleagues (2024) explore uncertainty in internal representations using a Bayesian Network model that fully parametrizes the agent's perceived position and landmark locations. These parameters are updated through noisy perceptions and actions, effectively replicating landmark-based wayfinding strategies under uncertainty [93]. Although this approach was applied to a simplified task (using landmarks only), it provides a valuable foundation for developing more complex wayfinding models that can account for the dynamics of human knowledge acquisition in unfamiliar environments.

3.4.7 Modeling Wayfinding Strategies (RQ2)

For complex wayfinding tasks, it is often insufficient to make rational route choices at each local intersection; the wayfinder also needs to apply an overarching strategy to reach their destination. This strategic aspect of wayfinding—sometimes called "**global strategies**" or the "planning layer"—involves high-level problem-solving to enact error correction, efficient exploration, respond to unanticipated obstacles or setbacks, and segment tasks into manageable steps [104]. In the modeling process, often these strategies are inserted as high-level heuristic rules, such as "first figure out how to get to the correct floor of the building," or "go back to the most visible area when getting lost."

Our review indicated that most of the wayfinding models that addressed complex, whole-building tasks integrated some type of global strategy layer. This often took the form of flowcharts, finite state machines, or other high-level rule-based algorithms. These important components of the models exhibited significant variation across studies, with no clear commonalities. Some of the strategies were relatively simple, such as proximity checks of surrounding agents or nearby exits to determine specific agent behaviors [124,125]. Others were more complex, integrating sequential assessments of leader presence, cognitive states, and numerous environmental factors to shape the agent behavioral path [110,120]. Some researchers drew from prior empirical studies to ground their global strategies. For example, Gath-Morad and colleagues (2020) included a strategy in which agents tend to move toward central areas with broad visibility [104].

The application of these strategies to shape simulated wayfinding outcomes is potentially concerning, especially since these guiding heuristics have little consistency from one study to the next and often seem to be inserted at the whim of the programmer. More work is needed to put these approaches on solid empirical footing and to develop a consistent set of high-level modeling practices.

Local strategies, by contrast, focus on optimizing decision-making at each timestep. These strategies include avoiding obstructions [83], vector-based movement [93], the follow-the-nose heuristic [126], knowledge [92], random choice [127], and integrating information from multiple sources through methods like mixed logit models [68,101,119] or information fusion techniques [30]. Rule-based approaches are also frequently used to model local behaviors. For example, some models incorporate real-world data to approximate actual behavior distributions, transforming deterministic rules into probabilistic ones, such as deciding whether to follow signs or crowds [118].

3.4.8 Validation (RQ3)

Among the reviewed articles, 27 (54%) lacked any form of validation to determine if the simulated agent behaviors reflected actual human wayfinding. The remaining 23 studies included various types of validation with different degrees of robustness. We identified three primary forms of validation used in these studies: (a) validation datasets, (b) behavior replication, and (c) qualitative validation.

14 studies used one of the strongest approaches to validate wayfinding models for a particular human population is to use **validation datasets** that are independent of the model's development and calibration processes. In this approach, novel empirical data from human wayfinders is used to compare against the model's outcomes in identical environmental settings. This makes it possible to quantitatively compare human vs. agent behaviors across metrics such as evacuation time [105], trajectories followed [93], travel distances [80], route usage [88], and route choice accuracy [68,101]. The use of validation datasets is the gold standard for rigorous model assessment, but it requires the availability of high-quality human behavioral data, which can be logistically difficult to obtain.

8 studies used **behavior replication** that compared model behaviors with prior wayfinding studies. Researchers may assess whether or not the simulated agents are exhibiting "human-like" behaviors, such as bottleneck congestion or herding tendencies [84,96,99,108,110,116,117]. This method is particularly common in crowd evacuation studies,

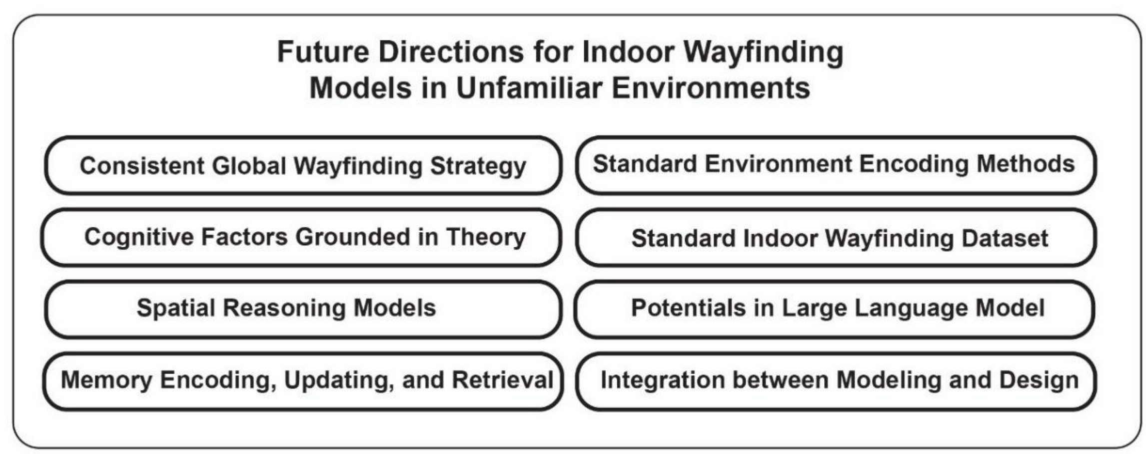
where there is an abundance of observational literature about how masses of humans have behaved in real-world scenarios, as well as significant logistical and ethical challenges associated with producing novel quantitative validation datasets. In the absence of numerical validation, researchers can demonstrate the plausibility of their models by showing that they replicate well-studied behavioral phenomena.

Finally, **qualitative validation** has been used in 1 study to analyze differences and similarities between agents and human wayfinders. This method involves observing and thoughtfully comparing agent behaviors against human behaviors in a descriptive fashion [95]. While it is less precise than quantitative validation, this approach may allow researchers to identify more subtle issues in the simulation and provide insights for improving the model's accuracy. It is particularly common in small-scale exploratory studies or when detailed quantitative data are unavailable. Even when more robust quantitative validation metrics are used, careful observation of agents can be a valuable supplement to help in interpreting the *reasons* for performance discrepancies and to indicate potential directions for model improvement.

3.5 Discussion and Future Works

Our review intended to assess the overall prospects, challenges, and provide future directions for developing realistic models of indoor wayfinding in unfamiliar environments (Figure 8).

Figure 8 Future Directions of Indoor Wayfinding Models in Unfamiliar Environments



One important finding in this regard was that the studies demonstrated a **tremendous inconsistency as well as oversimplification in applying global wayfinding heuristics.** 12 (24%) of the reviewed articles relied on shortest-path or adapted-shortest-path algorithms to determine the agent routes. Such approaches may be marginally defensible for crowd evacuation scenarios, but they cannot reflect the realities of human behavior in more complex wayfinding tasks. While many studies applied more complex global heuristics to govern agent behavior, no significant consistency was found across different studies [102,104,110,111,120]. It seems reasonable to suggest that nuanced indoor wayfinding behaviors in unfamiliar environments such as backtracking, exploration, error recovery, and learning cannot be adequately modeled without the application of (a) smart local-decision and perception frameworks that allows such high-level planning to emerge, and/or (b) global models that are highly nuanced and grounded in cognitive theories and empirical study.

We also found that **very few wayfinding models incorporate spatial reasoning.** The vast majority of the simulations in the reviewed literature failed to include any form of decision-making based on architectural design features. This is interconnected with the simulations' tendency to rely on abstracted and oversimplified spatial representations, for example by reducing the wayfinding environment to a node-and-path schematic. Spatial features such as color, lighting, ceiling height, and furniture layout are profoundly salient in human wayfinding performance [128]. We found that it was common in the reviewed studies to either ignore these features altogether, or else to roughly abstract them into discrete categories in an inconsistent fashion [66,68,89].

Further compounding this issue, the reviewed studies almost entirely neglected the topic of spatial schemas—preconceived mental representations of a building's layout—that are essential for navigating unfamiliar spaces [129]. For example, most wayfinders have a well-established concept of what a lobby is, and recognize distinctions between staff areas vs. public areas. Humans draw from theses schemas and others when interpreting spatial cues during wayfinding. Of the reviewed studies, only one addressed such logical spatial associations [104]. Future empirical and modeling studies should explore wayfinders' prior spatial schemas, how humans utilize these schemas when making route choices, and how these schemas evolve over time.

Advanced environment encoding techniques set the foundation for modeling spatial reasoning, such as hierarchical graph, isovist-based, and point-cloud environment encodings, better mimic human visual perception but often introduce extraneous information and computational complexity [91,102,130]. Future research should develop standardized environment encoding methods that capture both structural and experiential spatial aspects.

We found that existing wayfinding models tend to **poorly reflect human memory encoding, updating, and retrieval**. Only six studies (12%) made efforts to model familiarity and cognitive map formation. Some studies explore familiarity updates and knowledge spreading [92], only one investigates the formation of distorted cognitive maps from exploration [91], and another examines uncertainty in landmark-based navigation [93] These isolated efforts have yet to sufficiently generalize map-updating mechanisms for building-scale wayfinding in unfamiliar environments. Future research should focus on developing computational frameworks grounded in cognitive theories to model the dynamic interactions involved in constructing and refining cognitive maps, which would bridge the gap between human-like exploration and existing deterministic approaches.

Cognitive factors, such as panic and stress, are frequently modeled in evacuation scenarios, but these reactions and other **cognitive factors remained mostly unexamined in regular (non-emergency) wayfinding models.** While emotions may not be as strongly felt in everyday wayfinding compared to evacuations, they nonetheless have an important role in behaviors such as information-seeking, exploration, and route selection [3,4,6,18,131]. Incorporating feedback loops for cognitive factors such as uncertainty, curiosity, and anxiety could potentially improve the realism of indoor wayfinding models and provide insights for designing more welcoming built environments.

Another crucial concern that emerged in the literature review is a **lack of robust empirical data on indoor human wayfinding.** Such data is highly useful for constructing wayfinding simulations and validating their accuracy, but it can require significant research effort and expense to obtain. With broader datasets, it would become more feasible to incorporate real-world human parameter distributions into the simulation models (that is, a better representation of the diversity of human agents that exist in real-world contexts) [67,132,133]. At the current time the field lacks such large-scale standardized datasets of indoor human wayfinding behaviors, particularly those annotated with spatial and environmental features. It would be beneficial for future research efforts to prioritize the development of publicly accessible data with standardized protocols and formats to enable robust, data-driven modeling and validation.

It seems likely that researchers who are interested in wayfinding simulation may wish to take advantage of the current **rapid growth of large language models (LLMs) for representing spatial reasoning and route selection.** In the current review we found only one such study, conducted by Dang and colleagues (2024) [97]; however, it would be surprising if more were not soon to be published. LLMs are able to process wide contextual information and simulate "human-like" decision-making. We recommend caution in this area, however, since LLMs face notable limitations. Their lack of inherent spatial awareness hinders their ability to reason about geometric or topological relationships [134,135], which are essential for accurate wayfinding simulations. Additionally, their decision-making processes are not transparent, relying on patterns in training data rather than grounded cognitive mechanisms, which means that they may be prone to aberrant behaviors that poorly reflect human outcomes. Robust validation against novel human data becomes even more important when relying on LLMs, and the ability of these models to accurately and consistently predict human behaviors may be limited [136].

Finally, we need **a stronger feedback loop between modeling and design practice.** One of the overall limitations of the wayfinding simulation approach is that when designers introduce highly novel architectural ideas, the models may lack the basis for accurately predicting how humans will respond to those innovations. Human behavior constantly adapts to new environments and to cultural changes, while models are based on past trajectories and established knowledge. The risk is that models may inadequately evaluate both the values and drawbacks of unconventional designs. Thus, it is important to recognize that the feedback gained through simulation is a stepping stone and an aid in critical analysis, not a rigid straightjacket constraining design. An effective approach to using simulation tools in creative design practice might involve systematically introducing novel design variables and scrutinizing the outputs to inform the designer's reasoning. In turn, designers can help to enhance the accuracy of simulations by reporting questionable outcomes, which may need to be subjected to empirical testing, with the models updated based on the results. This reciprocal process or feedback loop can encourage innovation and adaptability in the field, ensuring that models continue to evolve alongside real-world practices. Establishing such a feedback loop will require interdisciplinary collaboration and systemic efforts, which future researchers can beneficially pursue as part of their intellectual trajectories.

3.6 Conclusion

This literature review highlights successes as well as important gaps in the current state of indoor wayfinding modeling. Existing models often rely on simplistic wayfinding strategies, limited environment encoding, and static assumptions about human cognition and memory, all of which fail to capture the dynamic nature of real-world human wayfinding, especially in complex and unfamiliar environments. The under-utilization of first-person perceptual models in these simulations, and the lack of comprehensive datasets of human outcomes to inform and validate them, further constrains their development and impact. To advance the field, we recommend that future research should prioritize simulations that robustly encode environmental features, integrate cognitive states and spatial reasoning, and dynamically model human learning and memory processes. Finally, fostering a beneficial feedback loop between modeling and design practice can help bridge the gap between theoretical insights and real-world applications.

This study advances automation in construction through the enhancement of computer-aided design and engineering tools, the development of more effective decision support systems, and creating precise models of human behavior, ultimately enabling the automated design of buildings optimized for intuitive and efficient human navigation.

Chapter 4. Real-time Continuous Perceived Uncertainty Annotation for Spatial Navigation Studies in Buildings

4.1 Abstract

In order to study the complex psychological processes involved in human wayfinding in increasingly complex built environments, it is crucial to have continuous self-report measures. In this study, we developed two different methods for continuously measuring perceived uncertainty during wayfinding, one is real-time continuous annotation (RCUA) using a joystick device and the other is post-hoc continuous annotation (CUA) involving annotations while watching video footage of recent wayfinding activity. To evaluate the usability, reliability, and validity of both approaches, we conducted a study with 54 participants. We assessed the measures' reactivity during different sign-seeing events. We also evaluated the convergent validity of both measures by comparing their outcomes with a self-report questionnaire, and assessed their discriminative and predictive validity by comparing uncertain values between known groups and correlating those values with wayfinding performance. Our findings suggest that both approaches were valid at the task level, but RCUA was better at capturing fine-grained dynamics of human experience. These continuous uncertainty measures can provide valuable insights into the fleeting nature of human experience and help identify "problem spots" for wayfinding in complex buildings.

Keywords: Perceived Uncertainty, Wayfinding, Continuous Annotation, Human Building Interaction

4.2 Introduction

Wayfinding, the process of determining and navigating a path to a desired destination, is an essential daily activity [1]. However, with the increasing complexity of built environments and a growing aging population, the challenges tied to wayfinding have become notably salient [137].

While there are numerous wayfinding aids like signs and maps, perceived uncertainty remains a prevalent experience throughout the navigation process. This uncertainty often stems from a lack of clarity about forthcoming events [131,138]. Such feelings can be evoked by encountering ambiguous, unreliable, or conflicting information during navigation [4,5,139,140], or simply being at a complex intersection without signs [102].

Some theoretic frameworks have been proposed to describe uncertain feelings. The Entropy Model of Uncertainty (EMU), developed by Hirsh, Mar, and Peterson (2012), drew inspiration from information theory's concept of entropy and applied it to psychology. The EMU posits that when faced with increasing uncertainty, cognitive structures are either adjusted or developed to regulate this internal 'entropy'. Without these structures, the system might get overwhelmed, potentially leading to degradation. This perspective is rooted in the idea that a pivotal role of the nervous system is to reduce entropy and unpredictability [9]. The EMU model identifies two main facets of Uncertainty: (a) perceptual uncertainty related to sensory input, and (b) behavioral uncertainty related to the selection of action/behavior [4]. Both of these domains are relevant to wayfinding research.

Another useful analytical framework proposed by Bach and Dolan [7] consists of four cognitive stages where uncertainty can arise: (1) sensory processing, (2) state evaluation, (3) rule identification, and (4) outcome prediction. For example, imagine a person encountering a worn-off sign during the wayfinding process. The person starts with uncertainty about the visual sensory information: "Is it room 101 or room 701?" This reflects uncertainty due to noisy sensory input. The second process, state evaluation in the wayfinding context, involves answering the question, "Where am I at this moment?" Then, assuming the person enters the elevator. Upon discovering the confusing elevator buttons labeled "T", "G", "1", the person might be unsure about how the numbers correspond to the floor levels, reflecting uncertainty in rule identification. Finally, if the person is faced with two identical-looking corridors, this reflects uncertainty in the outcome prediction phase, as the person has to estimate the probability of reaching the destination for each choice. The overall state uncertainty can be the aggregation of uncertainty from all four processes.

Uncertainty is an important mediator between environmental features and wayfinding behaviors or experiences. Uncertainty states in wayfinding are linked to behaviors such as heightened information-seeking [141] and more risk-averse wayfinding strategies [140]. Anderson and colleagues [131] presented that experiences of uncertainty can also be linked to stress, anxiety, and feelings of insecurity, which may affect the long-term mental health. Despite the importance of uncertainty states in wayfinding, there is currently no validated tool to measure it continuously.

4.2.1 Continuous Self-report Measure for Behavioral Studies

Though wayfinding process is a continuous, dynamic, and interactive process between human and the environment [65], most existing metrics of wayfinding behaviors are *discrete* in the sense that they measure wayfinding outcomes at the task level. For example, previous researchers have measured the completion time of wayfinding tasks ([142], distance traveled [143–145], and the number of mistakes made during path selections [146]. Other approaches for studying wayfinding cognition included evaluating participants' success in directional pointing tasks [147], the ability to remember landmark sequences [148], and drawing trajectories [149]. Such approaches are useful, but they can't capture the dynamics during the continuous process of wayfinding. Therefore, we need new measures to investigate moment-to-moment fine-grained wayfinding behaviors.

Compared to discrete post-stimulus measurements, continuous evaluation offers advantages. When the data are self-reported, continuous reporting is generally less intrusive and less likely to suffer from response biases or to interrupt the participants' experiences of the phenomena being studied [150]. Discrete measurements are most useful for short-duration stimuli that do not unfold through time, such as a still image [151,152]. In contrast, continuous measurements can provide data about changing human responses during ongoing behavioral processes, as is the case for wayfinding activities.

In recent years, wayfinding researchers are increasingly using novel tools such as eye-tracking [153], electrodermal activity (EDA) [154], and electroencephalography (EEG) [155,156] to study continuous human perception, affective responses, and cognition. These methods require precise linkage to psychological states, which has yet to be achieved. The current research addresses this gap, allowing for studies with detailed temporal resolution of the complex interactions among environmental factors, human cognition, behavior, and wayfinding performance.

The approach that we developed for measuring perceived uncertainty was loosely based on continuous self-report measures that have been used in other types of behavioral research such as studies of music reception, affective computing, and interpersonal interactions [157–164]. The common approach in these studies was to ask participants to engage in a continuous task, such as watching a video or engaging in a conversation, while simultaneously using some type of hand-held controller to continuously report the variable of interest.

One issue in such approaches is that the continuous response reporting may divide the participants' attention by increasing cognitive or physical load [165–168]. This problem was most notable when using physical devices such as mouse that required users to make constant adjustments. For this reason, researchers have gravitated toward the use of joysticks that include a return spring and thus automatically realign to the center in the absence of force [152,165,169]. This creates a more intuitive response-interface in which the user does not need to devote any specific cognitive attention to evaluating the position of the controller, but only needs to be aware of the amount of force applied. We adopted this approach by using a joystick device for our Real-time Continuous Uncertainty Annotation (RCUA). Moreover, as the older adult is one increasing population of wayfinding research, we investigate if older adults have challenges in using RCUA.

An additional concern in wayfinding tasks is that participants should not be visually distracted by the response interface, as they will need to have their full visual focus available to perceive the environment in a natural fashion. (This is not necessary when participants are, for example, listening to music or engaging in conversations.) In most of the prior studies that involves continuous self-reported measures, participants were shown the values that they were reporting in real-time on a display screen, which allowed them to make adjustments based on that visual feedback. The use of a joystick in natural environments eliminates the feedback display, but this introduces potential concerns about response accuracy [170]. To address this concern and evaluate the impact of eliminating visual feedback, we developed a second type of Continuous Uncertainty Annotation (CUA) that was not conducted in real-time. For the CUA measure, participants were first asked to complete wayfinding tasks, and then they watched the first-person video of their endeavor, while using a physical slider to annotate how uncertain they felt during the experience. In this approach the participants were susceptible to greater memory bias but they could see the exact value of Uncertainty that they were reporting displayed on the screen.

4.2.2 Research Aims

Validity of RCUA and CUA. We studied the continuous measures' discriminative validity at the wayfinding task level (H1) and the fine-grained sign-seeing level (H2) by using known groups [171]. We examined whether the metrics predicted wayfinding performance (H3). To establish convergent validity [172], we compared the uncertainty metrics derived from the RCUA and the CUA with a self-report uncertainty questionnaire (H4). Finally, we assessed the similarity between RCUA and CUA metrics (H5). Therefore, we hypothesized that:

H1: Novice wayfinders will report higher uncertainty for wayfinding tasks in comparison to Trained wayfinders and Expert wayfinders using the RCUA and the CUA.

H2: Participants will report less uncertainty after seeing a sign with directional guidance of the task, while they will report the same or higher Uncertainty after seeing signs without directional guidance using both RCUA and CUA.

H3: Higher uncertainty levels as reported by the RCUA and the CUA will be associated with longer wayfinding task Completion Times and greater Distance Traveled.

H4: Participants' discrete uncertainty levels on a self-report questionnaire will be correlated with their RCUA and CUA measurements.

H5: Responses on the RCUA and the CUA for the same wayfinding task will have no significant differences for similar uncertainty metrics.

Reliability of RCUA and CUA. To understand how well participants are able to consistently report desired uncertainty level using RCUA, we asked participants to repeatedly report among four levels of uncertainty by exerting different amounts of pressure on the joystick under three mobile conditions. We hypothesized that:

H6: There will be significant differences in the RCUA values between the four levels of uncertainty (“None,” “Slight,” “Moderate,” and “Extreme”), during all three conditions.

Usability of RCUA. One of our concerns was to determine if participants would be able to successfully use the RCUA joystick to report Uncertainty levels during an active wayfinding task, and if they could do so without excessive distraction from the wayfinding task. To this end, we asked participants to self-report their perceived cognitive load and how often they had forgotten to use the joystick after the wayfinding tasks.

4.3 Methods

This reliability, validity, and usability study consisted of three main steps. First, we test the RCUA’s reliability by measuring how consistently the participants were able to report different levels of uncertainty using the joystick device under a variety of conditions. Second, we asked participants to use the device to continuously report how uncertain they feel about the decisions they were making at that moment while completing several wayfinding tasks inside a building. This allowed us to evaluate the construct validity, discriminative validity, and predictive validity of the RCUA. Finally, we asked the participants to review a first-person video of their wayfinding activities immediately after completing them, during which time they provided the CUA annotation. This allowed us to evaluate the validity of the CUA and compare its results against the RCUA. We explain the details in the Procedure section.

4.3.1 Procedures

Prior to the experiment sessions, participants were asked to complete an online survey that collected demographic information along with responses for the spatial anxiety and self-report sense of direction. When participants arrived in the lab for their sessions, the researchers administered the Montreal Cognitive Assessment (MoCA) [173] and the Mental Rotation Test. After completing these enrollment surveys, the participants were asked to finish Parts 1–3 of the experiment as described below.

Part 1: Training. In this portion of the experiment, which we called the “Repeated Push,” participants were instructed to use the joystick to report four levels of uncertainty (“None,” “Slight,” “Moderate,” and “Extreme”). First, they were allowed 5 to 15 minutes of practice with a computer-based training program, which provided visual feedback regarding the joystick push level (as both a progress bar and a number). After the training, the researcher randomly asked the participants to report a particular level of uncertainty without visual feedback. This was repeated 8 times (twice for each uncertainty level), for each of three conditions: (a) seated in the lab before any wayfinding tasks, (b) walking through the lab before any wayfinding tasks, and later (c) walking through the lab after completing all wayfinding tasks. The purpose of this activity was to determine if the participants could accurately use the joystick to report the intended uncertainty level.

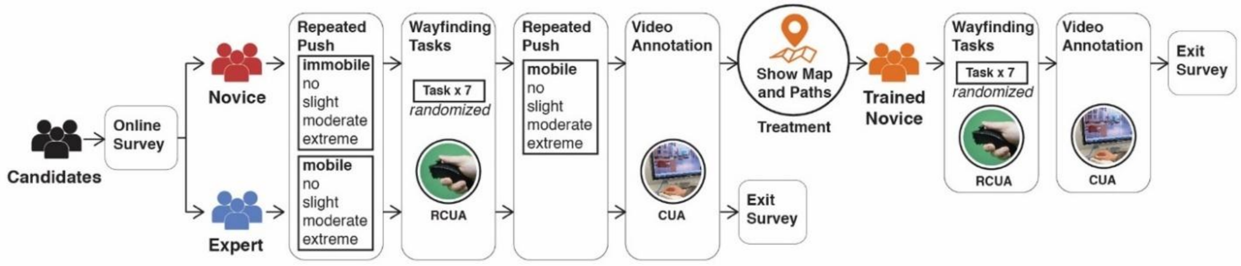
Part 2: RCUA Annotation. All participants, including Novice, Trained, and Expert wayfinders, were asked to complete the same wayfinding tasks in the same two interconnected buildings on campus, which are connected through a commons area. The connection of an old building that has undergone multiple rounds of renovation with a new building make this environment very complex for wayfinding. The building has received numerous complaints about the difficulties of finding destinations in this environment, making it ideal for studying uncertainty in indoor navigation. The study participants were asked to find seven specific destinations within the buildings in a set sequence (Figure 11). During each wayfinding task, the participants used the RCUA to continuously report their perceived uncertainty level. After participants complete each wayfinding task, they were asked to report their overall perceived Uncertainty level of the task using a self-report questionnaire, and report their task load. They were then informed of their next wayfinding goal. After finishing all the tasks, the participants and researchers returned to the lab, conduct CUA annotation and self-report the level of wayfinding interference using the RCUA.

Part 3: CUA Annotation. In the lab-based annotation, participants relied on their memory of the recent wayfinding tasks and used the CUA slider to indicate levels of uncertainty while watching first-person video taken from their body-cam. The current value of the CUA slider was displayed at the top-right corner of the screen during the video, so that the participants could observe their input. To reduce the length of the experiment sessions and avoid participant fatigue, and potentially to help reduce response bias, the video was played at 2x speed while participants made these uncertainty annotations.

Special Procedure for "Trained" Wayfinders. The "Trained" participant group was asked to undertake a somewhat different and more arduous procedure. This group participated in Parts 1, 2, and 3 of the experiment as Novices, as described above. After doing so, however, they were asked to return to the on-site buildings and complete Parts 2 and 3 again, after looking at a printed map with all destinations and shortest paths highlighted. Reviewing the map served as a known treatment, as this has been shown to improve wayfinding performance in multiple studies [174,175]. After examining the map, the Trained participants conducted all seven of the wayfinding tasks a second time with RCUA reporting, and then they returned to the lab and completed the CUA reporting a second time. A full summary of the experiment procedure is illustrated in Figure 9.

Part4: Sign Seeing Events Annotation. After the experiment, one researcher watched the first-person video recordings of the wayfinding process and annotated the sign seeing events. The starting point is marked when the participant stops and starts to read the sign. If the sign contains directional guidance of the task, it's marked as helpful. Since we found most participants finished reading the signs in ten seconds, wee extracted the RCUA and CUA values of ten seconds before and after the sign seeing events and excluded the events in which participants report zero uncertainty all the time. In total, 110 helpful sign seeing events and 185 unhelpful sign seeing events were extracted.

Figure 9 Experimental Procedure



4.3.2 Sample Size and Statistical Power

An a-priori power analysis of the required sample size was conducted using G*Power software for hypothesis one [176]. In order for comparison between Novice and Expert wayfinders, we need to assume mean and standard deviation for different groups. Though we were unable to find any prior literature on perceived wayfinding uncertainty that would provide assumptions for mean and standard deviation. we grounded our assumptions on the Hölscher (2006) study, which studied the frequency of becoming lost during wayfinding comparing novices (*M* = 0.42, *SD* = 0.17) vs. experienced participants (*M* = 0.17, *SD* = 0.21). Since we used seven wayfinding tasks for each participant, the inter-class correlation was assumed to be n = 7, phi = 0.5, and the design effect was assumed to be 1.3. The analysis suggested that we would need a minimum of 10 participants in each group to achieve a power of 0.8 for with an alpha of 0.05. Regarding the comparison between Novice and Trained wayfinders, we assumed a large effect size (d = 0.9) and the analysis suggested 13 participants to achieve a power of 0.8 for matched-pair analysis with an alpha of 0.05.

For other hypotheses (H2, H5, H6), we didn't conduct prior power evaluation. We conducted post-hoc simulation-based sensitivity analysis using the simr package in R [177] to evaluate the minimum effect size that our sample size will be able to detect with a power of 0.8.

4.3.3 Participants

Participants eligible for the study had to meet the following criteria: the ability to successfully perform wayfinding tasks in an indoor setting, including using stairs; no significant motor impairments; proficiency in understanding written and spoken English; and a score of 18 or above on the MoCA test, as administered by the researchers [173]. The MoCA was used to screen out participants who had possible cognitive impairments. A total of 54 participants were recruited for the study using a convenience sampling method.

Given the importance of age-related factors in wayfinding cognition (, we placed an emphasis on recruiting participants from across the adult human lifespan. The 54 participants who were included in the study ranged in their reported ages from 18 to 77 years old (*M* = 33.4, *SD* = 20.9), including fifteen participants (28%) who indicated that they were 60 years or older.

The final sample included 11 “Expert” wayfinders, designated as such because they were closely familiar with the two interconnected buildings that were used in the study (having visited the buildings a minimum of ten times and expressing confidence in giving wayfinding directions for the buildings). The remaining 43 participants had previously visited the buildings no more than once, and were designated as “Novice” wayfinders. From the pool of novices, 13 were randomly selected from the younger adults to become “Trained” wayfinders. This select group completed the wayfinding tasks twice, and before their second, “trained” attempt, they were allowed to review a floorplan-map of the buildings, on which the optimal routes for the study’s wayfinding tasks were highlighted. (Thus, the “Trained” group provided data twice, once as part of the Novice group and then a second time as Trained.)

When asked about their gender, 36 participants reported as Female, 17 as Male, and 1 as Other. Detailed distribution of gender of each group is shown in Table 1. Participant responses on the spatial navigation skills instruments are summarized in Table 6.

All participants gave informed written consent prior to the research activities, and the study procedures were reviewed and approved by the Institutional Review Board at Cornell University.

Table 1 Gender Distribution of Each Group. N: Novice, E: Expert, T: Trained

	Female	*Male*	*Other*
Old	*N = 9* *E = 1* *T = 0*	*N = 5* *E = 0* *T = 0*	*N = 0* *E = 0* *T = 0*

Young	*N = 19* *E = 7* *T = 9*	*N = 9* *E = 3* *T = 4*	*N = 1* *E = 0* *T = 0*

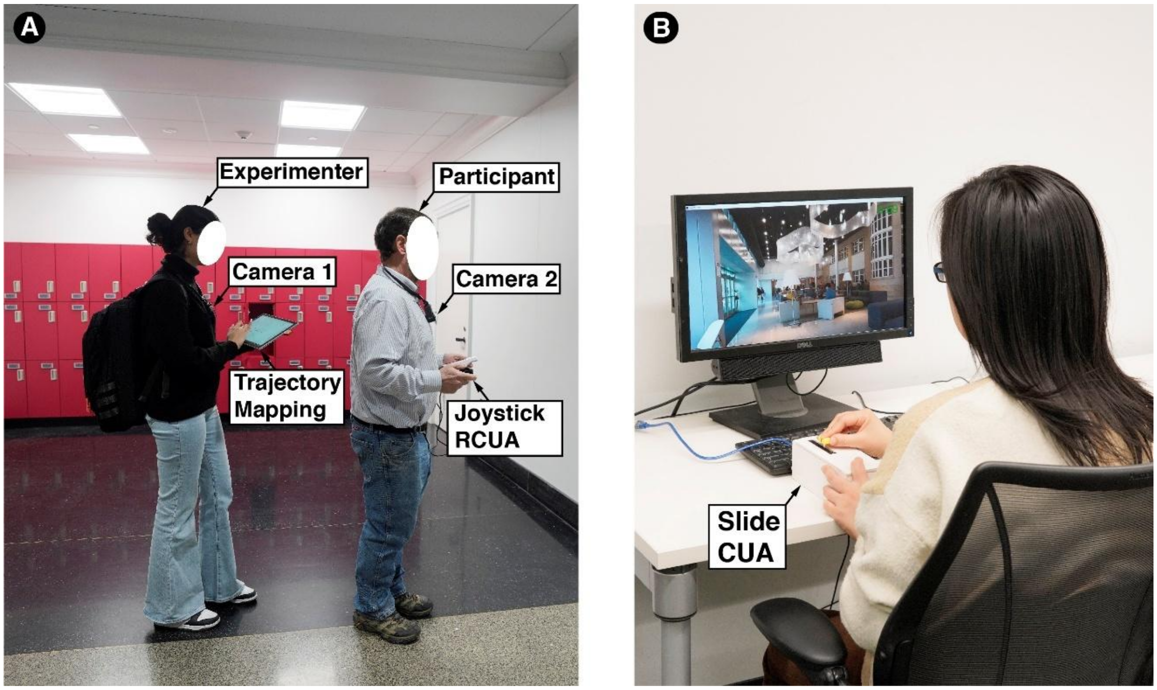
4.3.4 Hardware and Software Components of RCUA and CUA

The components of the RCUA and CUA were selected in such a way that they could easily be assembled and would be accessible to other researchers. For the RCUA joystick, we used a Nintendo Wii Nunchuk Controller paired with an 8BitDo Wireless USB Adapter (Figure 10a). The controller was chosen because it has a large analog stick, which is convenient for users to hold and push. In line with recent studies on human motor [178], we developed a script in the Python language that documented the real-time input of the controller in terms of the amount of force exerted in any direction from center. This allowed us to record a very simple and precise continuous metric of the user's reported uncertainty level, which we placed on a scale of 0 (no force / no uncertainty) to 1 (maximum force / maximum uncertainty). Participants were trained in the use of the joystick for reporting uncertainty levels prior to the wayfinding tasks, as discussed in the Procedures section above.

During the real-world wayfinding tasks, one or two researchers followed the participants at approximately 5–10 ft. distance, carrying a tablet computer (Microsoft Surface Pro). This computer received and recorded the wireless data from the joystick. Simultaneously, it ran the WayFind App previously developed by our team, which documented the participants' physical trajectories through the building over time. To create video of the wayfinding process, both the participant and the following researcher wore body cameras (GoPro Max), positioned at chest level. The participant's first-person video was used later in the CUA portion of the study, while the following researcher's third-person video was not used in the current analysis.

For the CUA metric we used a physical slider device, specifically the linear slide potentiometer module analog sensor. This selection was based on relevant prior work in video annotation [151,159], which has indicated that such a tangible device providing proprioceptive feedback is more effective for collecting participant reactions compared to mouse input. The slide-sensor was connected to an Arduino Uno board, which was contained within a white casing and linked to a standard desktop computer via USB-A (Figure 10b). We developed a processing script in Python that played the wayfinding video while documenting and synchronizing the real-time input of the slide. Similar to the RCUA, the slide input for the CUA was scaled from 0 (no uncertainty) to 1 (maximum uncertainty). The videos of the participants' prior wayfinding activities were presented on flat-screen displays with a resolution of 1920 x 1080 and a 60 Hz. refresh rate. Both RCUA and CUA data were down sampled to 5 Hz linearly. All of our software components have been made freely available for use by other researchers.

Figure 10 (A) Experiment Setting for Real Time Uncertainty Annotation (RCUA) during Wayfinding Tasks, and (B) Experiment Setting for Continuous Uncertainty Annotation (CUA) after the Wayfinding Tasks



4.3.5 Measures

Continuous Uncertainty. The continuous Uncertainty data recorded via both RCUA and CUA were operationalized into four levels: “No Uncertainty” (RCUA/CUA = 0), “Slightly Uncertain” ($0 < \text{RCUA/CUA} \leq 0.3$), “Moderately Uncertain” ($0.3 < \text{RCUA/CUA} < 1$) and “Extremely Uncertain” (RCUA/CUA=1). The data across an entire wayfinding task for one participant were summarized in five metrics: the total sum of reported uncertainty (S_U), the average uncertainty level (M_U), the total duration of uncertainty (T_U), the total duration of “Extreme” uncertainty (T_{EU}), and the frequency of uncertainty (F_U).

Self-report Task Uncertainty. The discrete task uncertainty questionnaire is adapted from the one used in the previous study [155] with 10 levels (1= No Uncertainty, 10 = High Uncertainty).

Task Load. We use NASA-TLX Questionnaire to measure task load (Hart & Staveland, 1988), which measures workload across six dimensions—mental demand, physical demand, temporal demand, effort, performance, and frustration—each has 10 levels, with higher scores indicating greater perceived task loads.

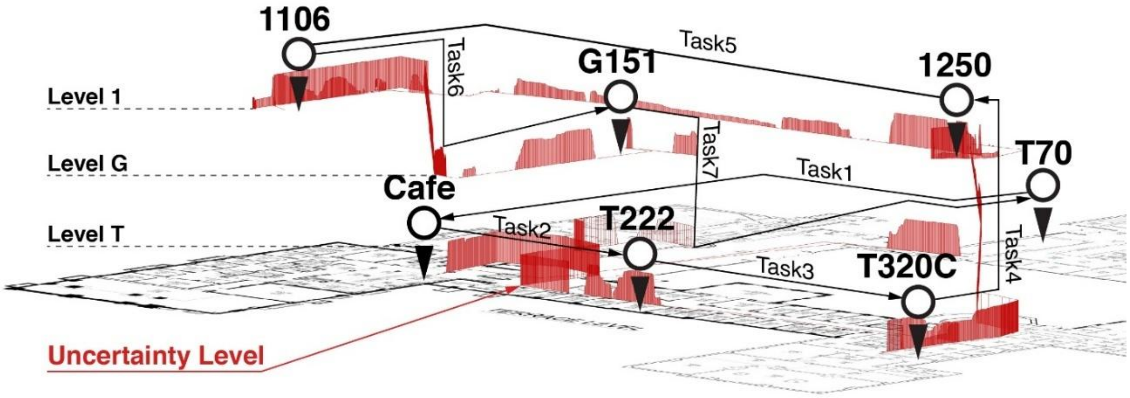
Cognitive Impairment. As noted above in the participant inclusion criteria, we used the Montreal Cognitive Assessment to screen for possible cognitive impairment, a factor that is particularly relevant for older adults. Scores of 17 or lower on the MoCA are regarded as an indicator of possible moderate or severe cognitive impairment and were excluded [173].

Spatial Anxiety. The Spatial Anxiety Scale (SAS) [179]was used to assesses participants' feelings of apprehension related to everyday tasks requiring spatial or navigational skills. This is an 8-item, 5-point Likert scale instrument in which higher scores indicate that the respondent associates greater anxiety with spatial tasks.

Spatial Abilities. Spatial abilities were also measured using the Santa Barbara Sense of Direction Scale (SBSOD) [180]. This is 15-item, 7-point Likert scale instrument in which higher scores indicate greater difficulty in spatial orientation, a factor that has previously been associated with wayfinding performance [142]. We also asked participants to complete the Mental Rotation Test [181], another metric commonly used to measure spatial ability. This instrument asks participants to mentally visualize rotating a three-dimensional object and to select the correct image from a list of options. Higher scores on this measure are interpreted as indicating greater spatial abilities.

Self-report Wayfinding Interference. We measure self-report wayfinding interference by asking the participants to rate the extent to which using the RCUA interfered with their wayfinding performance (1 = No Inference, 10 = High Inference). In addition, we asked participants to estimate the number of times they forgot to use the RCUA joystick to report uncertainty.

Figure 11 Map of the Seven Wayfinding Tasks, Showing the Physical Locations of Highest Uncertainty



4.3.6 Statistical Analysis

For discriminative validity (H1), we determined if there was a difference between novice and trained wayfinders by using a linear-mixed model in which participants experience, participant number, task, and the interaction between participant and task were used as random effects. Since comparison between novice and expert was a between-group comparison, besides random effects mentioned before, we added random effects including sense of direction and spatial anxiety. To test if uncertainty drops after seeing signs and if RCUA and CUA has different differences (H2), we averaged the uncertainty values before and after seeing signs and fitted a linear-mixed model in which annotation methods and time were used as fixed effect. Regarding predictive validity (H3), we firstly calculated the z-scores of the Uncertainty measures within each participant, and fitted a linear-mixed model to evaluate the intra-class correlation (ICC) between proposed measures and wayfinding performance metrics separately for each task, and determine the average. For convergent validity (H4), we used the similar method in H3 to evaluate the ICC between proposed measures and self-report uncertainty questionnaire measure. To test if RCUA and CUA provided different metrics for the tasks (H5), we fitted linear-mixed models to evaluate the significance of the fix effect of the measure on uncertainty metrics. To analyze the RCUA reliability (H6), we fitted linear-mixed models to evaluate if four levels of uncertainty were significantly different from each other. We included participant number as random effect, and included fixed effect of instructed uncertainty levels (no, slightly, moderate, extreme), and condition (pre-immobile, pre-mobile, post-mobile), and interaction. We repeated this model separately for younger and older adults.

We reported descriptive statistics of the NASA-TLX, self-report interference and number of forgets to demonstrate the feasibility and usability of the RCUA, to measure how RCUA matches CUA at the temporal level.

Since we were testing significance for five metrics (S_U, M_U, T_U, T_{EU}, and F_U) of RCUA and CUA in H1, we used Bonferroni correction to adjust our p-values.

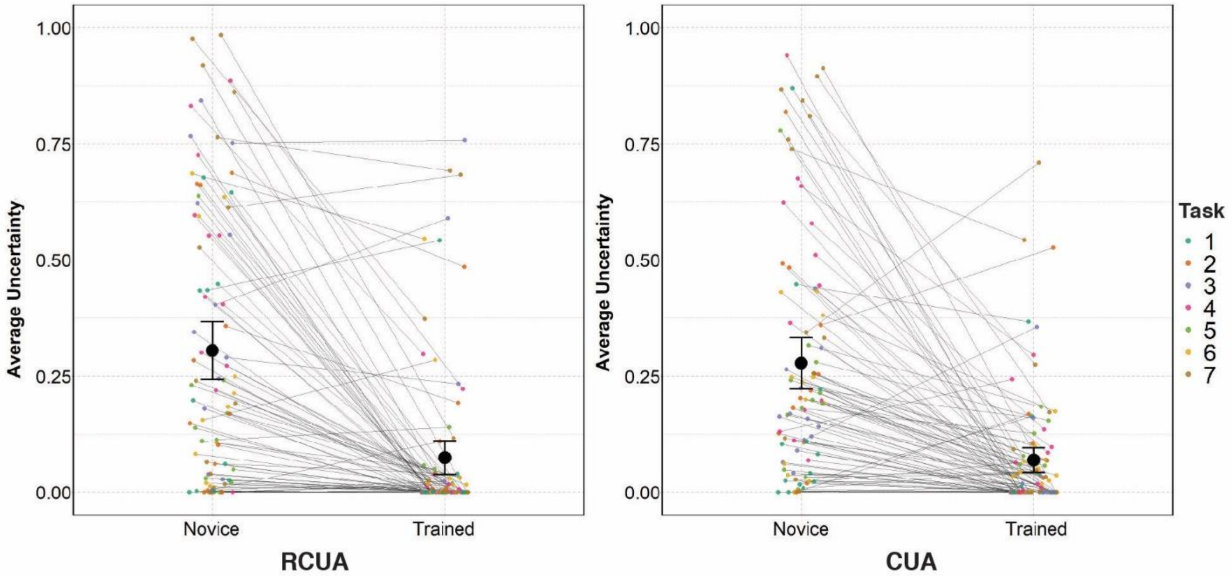
4.4 Results

4.4.1 Discriminative Validity of RCUA and CUA (Hypotheses 1)

We found significant differences between the scores of Novice vs. Trained wayfinders for all five discrete RCUA and CUA metrics (S_U, M_U, T_U, T_{EU}, and F_U). The metrics for Average Uncertainty (M_U) and Total Uncertainty Duration (T_U) had the largest effect sizes (Figure 12 and Table 2).

Regarding the comparison between Novice vs. Expert wayfinders, we found significant differences in the Total Uncertainty Duration (T_U) and the Frequency of Uncertainty (F_U) for the RCUA. For the CUA, we found significant differences for the Average Uncertainty (M_U), as well as for Total Uncertainty Duration (T_U) and Frequency of Uncertainty (F_U) (Figure 14 and Table 3). We did not observe any statistically significant differences in the spatial abilities and spatial anxiety between the "Novice" and "Expert" wayfinding groups, which means that they did not

Figure 12 Average Uncertainty Value (MU) of Each Wayfinding Task, Comparison between Novice Wayfinders and Trained Wayfinders



act as confounding variables in the study. These results were less decisive than the Novice vs. Trained comparisons. In summary, H1 is partially supported.

Table 2 Novice vs. Trained Comparisons for All RCUA and CUA Metrics

	t	*d*	*p*
RCUA			
Average	*7.902*	*1.67*	*< 0.0001*****
Sum	*5.952*	*1.25*	*< 0.0001*****
Duration	*7.314*	*1.54*	*< 0.0001*****
Extreme	*5.413*	*1.14*	*< 0.0001*****
Frequency	*7.606*	*1.61*	*< 0.0001*****
CUA			
Average	*7.410*	*1.56*	*< 0.0001*****
Sum	*5.522*	*1.16*	*< 0.0001*****
Duration	*7.852*	*1.66*	*< 0.0001*****
Extreme	*2.940*	*0.62*	*0.0041**
Frequency	*7.834*	*1.25*	*< 0.0001*****

*Note. p-threshold is 0.05 / 10 = 0.005 after Bonferroni correction. t: t-statistics. d: Cohen's d effect size. * significant after correction*

Table 3 Novice vs. Expert Comparisons for All RCUA and CUA Metrics

	t	*d*	*p*
RCUA			
Average	*2.739*	*0.81*	*0.0088*
Sum	*2.018*	*0.81*	*0.0494*
Duration	*3.047*	*0.91*	*0.0039**
Extreme	*2.457*	*0.73*	*0.0180*
Frequency	*2.869*	*0.80*	*0.0059*
CUA			
Average	*3.125*	*0.93*	*0.0031**
Sum	*1.828*	*0.54*	*0.0740*
Duration	*3.226*	*0.97*	*0.0024**
Extreme	*1.551*	*0.46*	*0.1278*
Frequency	*3.592*	*1.00*	*0.0007***

*Note. p-threshold is 0.05 / 10 = 0.005 after Bonferroni correction. t: t-statistics. d: Cohen's d effect size. * significant after correction*

Figure 13 RCUA and CUA Values Before and After Seeing Helpful vs. Unhelpful Signs

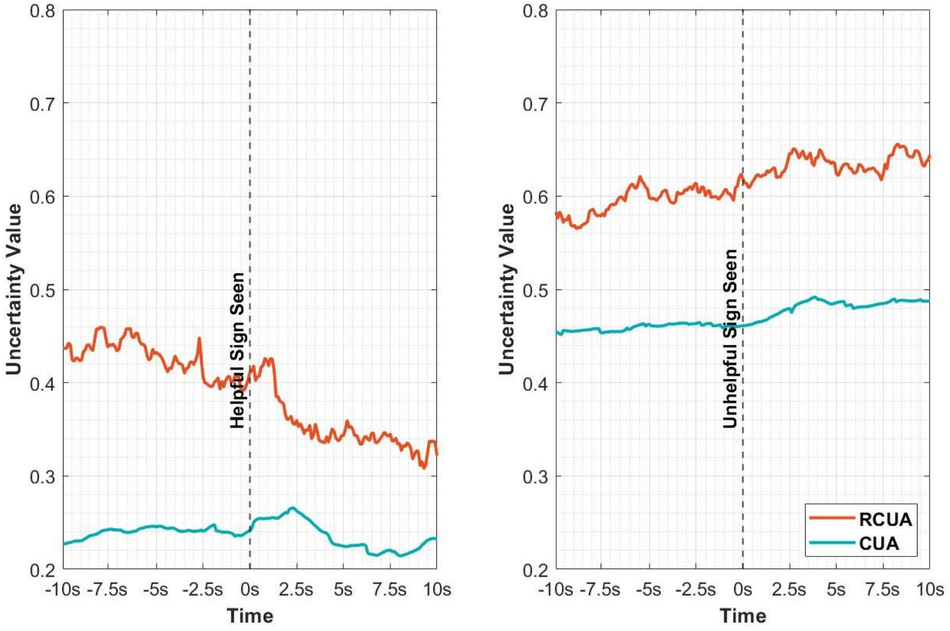
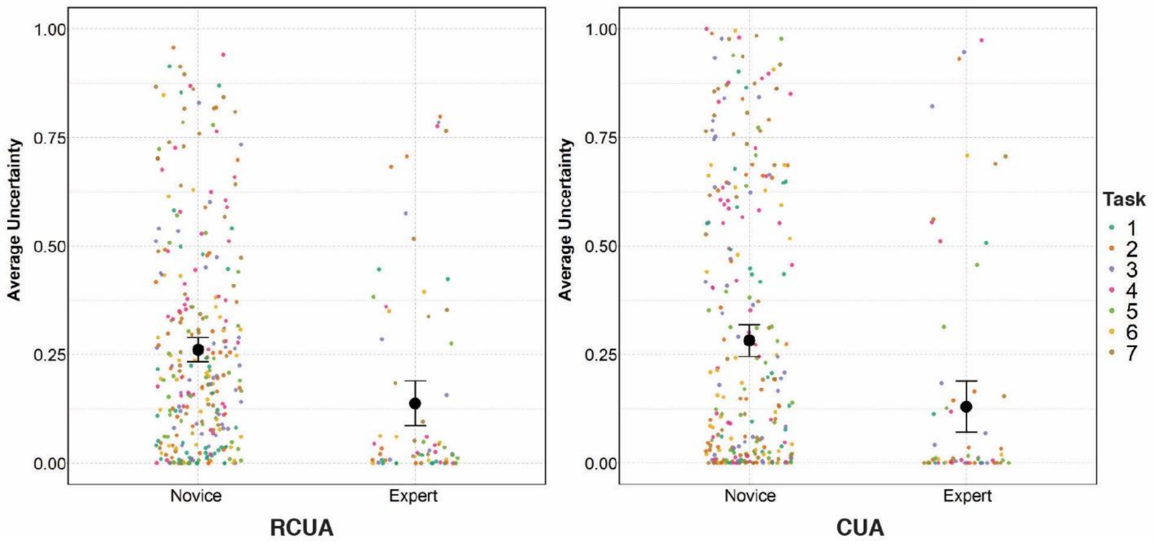


Figure 14 Average Uncertainty Value (MU) of Each Wayfinding Task, Comparison between Novice Wayfinders and Expert Wayfinders



4.4.2 Reactivity of RCUA and CUA Measure (Hypothesis 2)

We observed when participants approached and started to read the helpful signs, the uncertainty level continued to drop for the RCUA. However, uncertainty level of CUA remained relatively unchanged regardless whether the sign is helpful or unhelpful (Figure 13). We also noticed RCUA uncertainty values are higher than CUA uncertainty values in both sign conditions ($p < 0.05$). We found significant difference between the average RCUA uncertainty value before and after seeing a helpful sign ($t = 3.190$, $df = 218$, $d = 0.43$, $p = 0.0016$). We didn't find significant difference of CUA uncertainty value ($p = 0.851$). The post-hoc simulation analysis showed with our sample size, we had 80% power to detect a 0.037 decrease of CUA value as we go from before to after.

As for the unhelpful sign-seeing events, we found a small significant increase of RCUA values after seeing an unhelpful sign ($t = 2.531$, $df = 184$, $d = 0.37$, $p = 0.012$). We also find a significant increase of CUA uncertainty values ($t = 2.288$, $df = 184$, $d = 0.34$, $p = 0.023$). Therefore, Hypothesis 2 is supported.

4.4.3 RCUA and CUA Predictive Validity (Hypothesis 3)

The metrics derived from both the RCUA and the CUA showed moderate to strong correlation with the two wayfinding task-performance variables, Completion Time and Distance Travelled. For RCUA, the Sum Uncertainty (S_U) and Frequency of Uncertainty (F_U) metrics were the best predictors of wayfinding performance (Table 4). For CUA, the Sum Uncertainty (S_U) and Average of Uncertainty (M_U) metrics were the best predictors. H3 is supported.

Table 4 Intra-class Correlation Showing Relationships between Self-reported Uncertainty, Wayfinding Task Completion Time, Wayfinding Distance Travelled, and Five Metrics (SU, MU, TU, and TEU) Derived from the RCUA and CUA.

	RCUA				
	S_U	M_U	T_U	T_{EU}	F_U
Self-reported Uncertainty	*0.65*	*0.53*	*0.49*	*0.50*	*0.53*
Task completion time	*0.71*	*0.38*	*0.38*	*0.41*	*0.54*
Distance Travelled	*0.68*	*0.43*	*0.38*	*0.38*	*0.53*
	CUA				
	S_U	M_U	T_U	T_{EU}	F_U
Self-reported Uncertainty	*0.65*	*0.62*	*0.25*	*0.41*	*0.42*
Task completion time	*0.73*	*0.52*	*0.23*	*0.27*	*0.57*
Distance Travelled	*0.70*	*0.49*	*0.22*	*0.26*	*0.55*

4.4.4 RCUA and CUA Convergent Validity (Hypothesis 4)

Sum (S_U) and Average (M_U) for the RCUA and the CUA had a moderate intra-class correlation with self-reported uncertainty questionnaire (ICC > 0.5). The highest ICC were for the Sum Uncertainty measure of both the RCUA (r = 0.65) and the CUA (r = 0.65). Overall, these results indicate a high convergent validity between the results of uncertainty questionnaire results and the results of the RCUA and CUA; thus, H4 is supported.

4.4.5 Comparison of RCUA vs. CUA (Hypothesis 5)

We found significant differences between RCUA and CUA metrics in T_U and T_{EU} ($p < 0.001$). We did not find any significant differences between the RCUA vs. the CUA metrics regarding S_U, M_U and F_U. We picked the non-significant model with the largest effect size to run the post-hoc simulation analysis. It showed with our sample size, we had 80% power to detect a

0.038 decrease of CUA M_U value compared with RCUA, which is small. Therefore, H5 is partially supported.

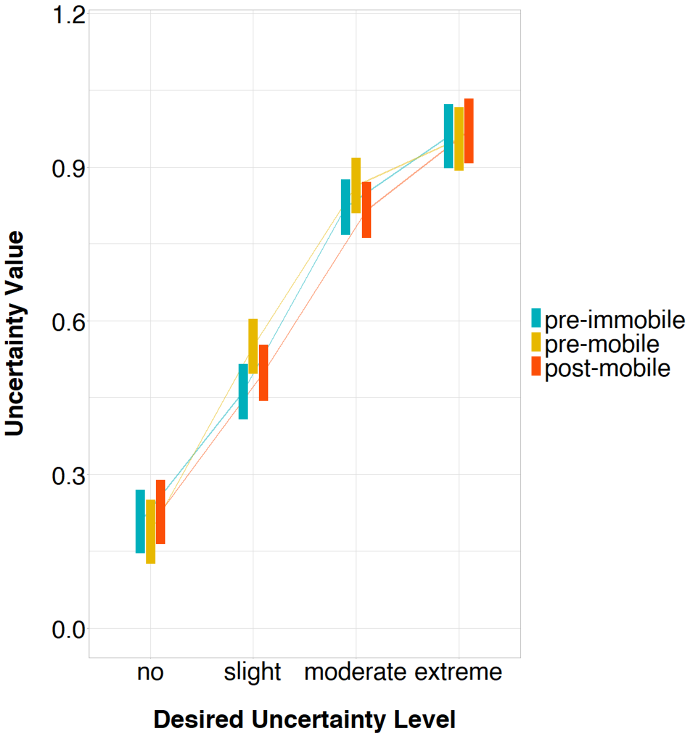
4.4.6 RCUA Reliability (Hypothesis 6)

In the “Repeated Push” section of the experiment, we found statistically significant differences between the RCUA joystick push values for the four levels of uncertainty reported (“None,” “Slight,” “Moderate,” and “Extreme”), for all three conditions in which we tested these responses (pre-wayfinding seated/immobile; pre-wayfinding walking/mobile; and post-wayfinding walking/mobile) (overall, F(3, 1114) = 345.64, $p < 0.001$). Except for the Moderate–Extreme comparison under the pre-mobile condition, the confidence intervals of adjacent Uncertainty levels did not overlap (Figure 15 and Table 5). Thus, H6 is supported.

Table 5 The 95% Confidence Intervals for Four Levels of Uncertainty (“None,” “Slight,” “Moderate,” and “Extreme”) Across the Three Experimental Conditions

	Pre-immobile	***Pre-mobile***	***Post-mobile***
None	*[0.145, 0.270]*	*[0.125, 0.250]*	*[0.164, 0.290]*
Slight	*[0.407, 0.516]*	*[0.496, 0.604]*	*[0.444, 0.553]*
Moderate	*[0.767, 0.875]*	*[0.810, 0.918]*	*[0.761, 0.871]*
Extreme	*[0.897, 1.022]*	*[0.892, 1.017]*	*[0.908, 1.034]*

Figure 15 The 95% Confidence Intervals of Peak Joystick Value when Reporting Four Levels of Uncertainty under Three Conditions



4.4.7 Feasibility and Usability of the RCUA

In regard to participants' real-time use of the RCUA joystick: 13% (n = 9) self-reported that they never forgot to use the device to report perceived uncertainty; 49% (n = 34) self-reported they forgot to use the device one or two times; 19% (n = 13) self-reported that they forgot to use the device 3–5 times; 13% (n = 9) self-reported they forgot to use the device 6–10 times; and 6% (n = 4) self-reported that they forgot to use the device more than 10 times. Since the average number of uncertainty changing events during each wayfinding task was 25.7, this level of non-reporting was within an acceptable range (approximately 4.08% overall).

Table 6 Individual Differences among the Study Participants

Scale	*Minimum*	*Maximum*	*Mean*	*SD*

All	*Mental Rotation (n = 53)*	*0*	*13*	*6.09*	*3.57*
	Sense of Direction (n = 51)	*2.4*	*6.4*	*4.33*	*0.98*
	Spatial Anxiety (n=52)	*1*	*4.75*	*2.55*	*0.85*
Novice	*Mental Rotation (n = 42)*	*0*	*13*	*5.95*	*3.57*
	Sense of Direction (n = 41)	*2.4*	*6.4*	*4.26*	*1.03*
	Spatial Anxiety (n = 42)	*1*	*4.75*	*2.56*	*0.91*
Expert	*Mental Rotation (n = 11)*	*2*	*13*	*6.64*	*3.72*
	Sense of Direction (n = 10)	*3.2*	*5.8*	*4.63*	*0.72*
	Spatial Anxiety (n = 10)	*2*	*3.88*	*2.54*	*0.58*

Note: Scale ranges were as follows: Mental Rotation 0–24; Sense of Direction 1–7; Spatial Anxiety 1–5.

Regarding the task load scores (NASA-TLX), participants reported a moderate level of mental task load (*M* = 4.87, *SD* = 2.58*,* 95% CI [4.17, 5.57]) and a low level of physical task load (*M* = 2.70, *SD* = 1.73*,* 95% CI [2.23, 3.18]). One notable result on this instrument is that participants also reported a high perception of success in using the device (*M* = 7.48, *SD* = 2.19*,* 95% CI [6.88, 8.08]) (Table 7). Our survey question regarding the interference of RCUA with wayfinding activities found a relatively low interference level (*Possible Range* 1–10, *M* = 3.11, *SD* = 2.04*,* 95% CI [2.55, 3.67]). Overall, these results indicate that individuals were able to use the joystick device during real-world wayfinding tasks without excessive workload or distraction.

Table 7 Self-reported Task Load (NASA-TLX Scores) for the Use of RCUA during Wayfinding

	Mean	*SD*	*95% CI*
Mental Demand	*4.87*	*2.58*	*[4.17, 5.57]*
Physical Demand	*2.70*	*1.73*	*[2.23, 3.18]*
Temporal Demand	*3.17*	*2.29*	*[2.54, 3.79]*
Performance	*7.48*	*2.19*	*[6.88, 8.08]*
Effort	*4.43*	*2.06*	*[3.86, 4.99]*
Frustration	*3.52*	*2.12*	*[2.94, 4.10]*

Note: All metrics in the table range from 1 to 10.

4.5 Discussion

This methodological research was conducted to help answer the call for better empirical study on human wayfinding processes, and specifically on the role of uncertainty during spatial navigation (Keller et al., 2020). We evaluated two different approaches to continuous uncertainty annotation during wayfinding, one in real-time (RCUA) and another using post-wayfinding video evaluation (CUA). The results of the study support the reliability and validity of both measurement approaches. The usability testing for the RCUA also confirmed that our participant sample, which notably included a large representation of adults aged 60 years and older, were able to use the joystick device during real-world wayfinding tasks without excessive workload or distraction.

4.5.1 Tools' Reliability and Validity

RCUA approach does not allow participants to see visual feedback displaying their current annotation input level, as is presented on-screen during the CUA annotation. We were concerned that this might lead to reliability problems for the RCUA if participants could not accurately and consistently use the device to report the uncertainty values that they intended to report. The reliability results (Table 5) showed this concern to be unfounded, as participants of all ages demonstrated great success in consistently using the RCUA joystick to report a specified uncertainty level.

The validity testing also yielded positive results for both instruments. In terms of convergent validity, the uncertainty measures collected via the RCUA and the CUA were strongly correlated with participants' reporting of uncertainty on a written Likert-scale instrument. Discriminative validity was evaluated by comparing the scores of Novice vs. Trained wayfinders and Novice vs. Expert wayfinders. The results indicated that both the RCUA and the CUA were able to distinguish between these groups, though they both had greater success distinguishing Novice vs. Trained than distinguishing Novice vs. Expert. This result is not particularly surprising, since in our group categories the "Trained" wayfinders received relevant route information immediately prior to the wayfinding tasks, while the "Expert" wayfinders simply had prior overall experience with the buildings. Thus, it is plausible to find that Trained group showed greater differentiation from the Novices than did the Experts. Finally, the results indicated that both the RCUA and the CUA had good predictive validity, as participants' scores on these instruments were able to predict their wayfinding performance in terms of task Completion Time and the total Distance Travelled while finding a destination. It is a reasonable assumption that this performance relationship is due to increased uncertainty being associated with an increase in pausing, backtracking, and information-seeking behaviors (Hirsch et al., 2012), which would increase the task duration and distance covered in the wayfinding tasks.

4.5.2 RCUA vs. CUA

The two measurement approaches that were evaluated in this study have different potential strengths and weaknesses. Though we did not find any significant differences between the RCUA and CUA uncertainty metrics for varied wayfinding tasks, the fine-grained analysis of sign seeing events (hypothesis 3) demonstrated that RCUA better captured fleeting real-time uncertainty experience compared with CUA. The result showed that multi-tasking and a lack of visual feedback didn't prevent most participants from using RCUA to report uncertain experiences in a timely manner. On the contrary, CUA measure omitted details because it relied on participants' memory and analysis of their prior activities. As for the amplitude between two methods, though we didn't find significant difference at the task level, sign seeing analysis showed that participants tended to report less uncertain experience using CUA. It could result from systematic underestimation due to memory bias and annotation setting, or participants overly reported uncertain experience using RCUA, which requires further examination. Combined with the finding of strong discriminative and predictive validity, both instruments can serve as effective approaches for measuring perceived uncertainty at the task-level resolution. However, RCUA better captured fine-grain dynamics of uncertain experience.

It is worth noting in this regard that the average time from the participants' completion of the wayfinding tasks to their completion of the CUA video-based reporting was about 37 minutes (*M* = 36.72*, SD* = 9.94, range: 18.55–67.22). It is possible that longer time intervals could reduce the accuracy of the CUA approach. Another vital component of the CUA is that participants were annotating videos of their own previous wayfinding activities (not a video of another person); the results of the current study should not be generalized to support video-based annotation made by observers.

Figure 16 One Application of the RCUA: Kernel Density Map Showing Uncertainty Distribution from All Participants of One Floor Level

4.5.3 Impact

The methods developed and evaluated here for wayfinding Uncertainty annotation can enable the collection of fine-grained, temporal data in real-world environments. In many wayfinding research [182–184], this approach can improve upon the classic discrete wayfinding metrics such as task completion times, travelled distance, or number of mistakes. For example, when evaluating wayfinding design strategies or considering renovations in complex buildings such as a hospital or an airport, continuous wayfinding annotation can enable rigorous scientific studies to compare the efficacy of different interior designs or signage strategies, or to locate problem spots within a building floorplan (Figure 16). For instance, areas that offer multiple route options and fewer signs tend to create a sense of uncertainty in people. However, it's not a straightforward linear relationship. Our observations indicate that encountering multiple uncertain areas consecutively, or encountering one suddenly after a period of clear navigation, intensifies people's perceived uncertainty. This suggests that precise signage location and spacing could significantly enhance wayfinders' confidence. Investigating the impact of sequential uncertainties on wayfinding presents a compelling direction for future research. This exploration could enhance decision support systems for layout design [185]. Another possible potential is to investigate individual differences in reactions to wayfinding Uncertainty and the associated behavioral. Such insights may provide the grounding for developing smart navigational aid systems that use physiological signals to classify human uncertainty states. In high-stakes situations, such as those involving emergency first responders or helping patients to reach the appropriate care centers, providing effective and appropriately intervention when wayfinding Uncertainty arises will be important.

In the broader trajectory of the human building interaction, continuous measures offer a comprehensive view of the human experience as it evolves over time, allowing researchers to track the dynamics of individual responses. These continuous insights form the bedrock for crafting temporal predictive models. Such models, with their ability to forecast human behavior and responses over time, herald a shift towards more human-centered interactions [74,186]. In summary, continuous measurement is not just a methodological choice but a paradigm shifts towards a more holistic understanding and facilitation of human-building interactions.

4.6 Limitation and Future Directions

Given the challenges in designing a mobile, self-reported continuous measurement system, there were naturally some limitations to our work. First, the temporal accuracy of the RCUA and CUA has not yet been fully validated. More scenarios besides sign-reading should be examined. Second, more work needs to be done to determine if the RCUA approach is suitable for research that requires other types of simultaneous participant action, such as reporting additional continuous variables, holding a map, or using a VR controller. The more multi-tasking that an experiment involves, the more likely it is that the effectiveness of real-time self-reporting may suffer. The validation results of the current study should not be extended to such contexts that place additional burdens on participants' attention.

The design of our experiment procedure also gives rise to some cautions and limitations. Participants conducted the CUA measure after the RCUA measure. Though participants were guided to self-report from memory, it's possible that they referenced their RCUA responses. The participants in the wayfinding study were followed by a researcher who carried various position-tracking and data-logging equipment. While the researchers tried to remain at least 5 ft. behind the participant at all times, their presence may have affected the Uncertainty measure from the participants, especially in regard to remembering to use the reporting joystick. Additional research is needed to determine if RCUA is effective during solo-wayfinding experiments. Another possible concern is that our evaluation of convergent validity was somewhat simplistic, relying on a single Likert-scale response after each wayfinding task to compare the RCUA and CUA data. The ability to better establish convergent validity is a bit problematic, as to the best of our knowledge there are currently no other scales measuring this continuous construct. However, the evaluation could be made more effective by using a more complex Likert survey and/or correlating uncertainty with related types of annotation such as “feeling lost.” Finally, we restricted the context of the study to in a large indoor educational setting, and did not test the uncertainty reporting in outdoor environments or other building types. We do not expect that such contexts will have a pronounced effect on the use of the CUA, but it is possible that environments with greater crowding or other distractions could negatively impact the real-time reporting of RCUA data.

4.7 Conclusion

The study investigated novel methods for measuring the continuous perceived experience in buildings, with a specific focus on the role of perceived uncertainty during spatial navigation. Two methods for continuous uncertainty annotation were developed and evaluated: Real-time Continuous Uncertainty Annotation (RCUA) and post-wayfinding Continuous Uncertainty Annotation (CUA). The study confirmed the reliability and validity of both methods, with RCUA being particularly effective in capturing real-time uncertainty, despite the lack of visual feedback for participants. Both RCUA and CUA showed strong convergent and discriminative validity, effectively distinguishing between different levels of wayfinding experience. Predictive validity was also demonstrated, as uncertainty scores predicted wayfinding performance metrics such as completion time and distance traveled. Notably, older adults successfully used RCUA without significant workload or distraction. The study highlights RCUA's superiority in capturing immediate perceived uncertainty, while CUA, reliant on memory, may miss finer details. This distinction is crucial for understanding the dynamics of perceived Uncertainty in wayfinding tasks.

The research has potential benefits not only for scientific inquiries in the dynamics of perceived wayfinding uncertainty in buildings, but also for the design and evaluation of navigational aids and building layouts. It also opens up possibilities for developing smart navigational systems and enhancing human-building interaction.

Chapter 5. PATH-U: A data-driven agent-based wayfinding model incorporating perceived path uncertainty and cognitive strategies in unfamiliar indoor environments

5.1 Abstract

As built environments become more complex, indoor wayfinding challenges increase, especially for first-time visitors. Effective wayfinding design and signage are crucial for helping people reach their destinations. Occupant simulations can analyze these features before construction and identify potential issues. However, current models for human wayfinding in unfamiliar environments are limited and rarely predict continuous experiences like perceived path uncertainty. This study developed an integrated agent-based model called "PATH-U," which simulates multi-floor wayfinding tasks without prior knowledge of the environment and provides feedback on uncertainty levels. This model is based on an observational study with 39 participants completing 273 wayfinding tasks in a complex university building. We developed a path-planning model incorporating visual perception, natural movements, short-term memory, heuristic strategies, and a data-driven multiple linear regression model for uncertainty prediction based on data from 28 participants. Validation with data from 11 participants under a different signage condition shows that the model mostly mirrors human wayfinding behavior and perceived uncertainty, with a few notable discrepancies. The findings suggest that wayfinding design should consider spatial dimensions, confirmational signage, and enhanced cues at crucial intersections to reduce uncertainty and improve performance. Future simulations should incorporate on-route behaviors and environmental reasoning.

Keywords: Perceived Path Uncertainty; Indoor Wayfinding; Data-driven Agent; Cognitive Agent, Simulation

5.2 Introduction

First-time visits to complex, unfamiliar buildings are among the most challenging of indoor wayfinding scenarios [1,64]. Directional signs play an important role in people's efforts to meet this challenge and reach their destinations. While adding more signs with clearer directions seems like an obvious solution, it can be difficult for designers to accurately evaluate visitors' needs and decide on a wayfinding signage strategy [187]. The complexity of this evaluation emerges from the vagaries of human perception, reasoning, and decision-making, along with the large variety of signage options that can potentially be used [188,189]. The desire to provide greater navigational information in diverse formats at every intersection has to be weighed against financial expense and the confusion caused by excessive visual clutter [190].

In response to this challenge, researchers have sought to create human wayfinding models for designers to gain early feedback on their work prior to construction. Currently, most of these models are focused on evacuation or traffic-flow scenarios, with few addressing first-time indoor semi-guided wayfinding contexts. Furthermore, existing models predominantly use task-level wayfinding performance metrics, such as total distance traveled and time required to reach a destination, which may not fully capture wayfinding experiences or readily pinpoint specific problem spots [80,191,192]. Limited models provided high-resolution spatial-temporal metrics, such as perceived path uncertainty, which identified when and where individuals feel uncertain. The current project was grounded in the view that high-resolution spatial-temporal metrics, such as moment to moment perceived path uncertainty while searching for a destination, can offer more precise feedback and insights to designers. Our work makes the following specific contributions:

- We present an integrated model called "PATH-U" (Predictive Agent for Testing Human Uncertainty during navigation) that simulates multi-level, partially guided indoor wayfinding without prior knowledge of the environment. The model is grounded in empirical research with human participants and can provide a prediction of path uncertainty along a route, addressing gaps in existing models that provide only task-level performance metrics.
- The study advances spatial-temporal metrics for wayfinding design by identifying salient features associated with perceived path uncertainty and integrating them into a broadly applicable model. Our simulation offers insights for designers who are seeking to create effective wayfinding systems in complex indoor settings.
- The study advances the current path-planning model in indoor wayfinding scenarios with visual perception, natural movement, short-term memory, and wayfinding heuristics for multi-level tasks.

The paper is organized as follows: Section 2 provides a brief literature review of existing indoor wayfinding models and relevant cognitive theories. Section 3 clarifies the methods used in the current study. Sections 4 and 5 describe in depth the development of our model. Section 6 reports the validity assessment that we conducted for the model through comparison to novel human data. Section 7 presents a discussion of our findings and insights for design practice.

5.2.1 Related Works

Modeling human wayfinding behaviors involves several notable challenges. The model must adequately represent the environment, analyze humans' limited sensory perceptions of their surroundings, and approximate human cognition and decision processes [30,65,68,102,193,194]. Fortunately, these are active research areas, and several recent review papers offer comprehensive overviews of established methods [33,67,75,77]. Common model frameworks that have been used to model human wayfinding include one or combinations of Cellular Automata (CA) [103,195,196], Agent-based Models [111], Social Force models [84,86,197,198], Flow [199], Navigation Field [108], Discrete Choice Models [40,42,195], Rule-based approaches [65,102,193,200], Information Fusion [30], and Data-driven approaches [42,194,201]. Our approach was based on the Agent-based Model (ABM) and Data-driven approaches. ABM simulates the actions and interactions of individual agents, each following defined rules, within an environment. This approach is ideal for modeling heterogenous microscopic behaviors in wayfinding. Data-driven approaches allow for more realistic environment initialization and behavioral rules [67,133]. While generally adhering to ongoing modeling practices in this area, we focused on adding a high-resolution spatial-temporal metric (moment-by-moment path uncertainty), grounded in an empirical study and analysis of cognitive factors affecting wayfinding behavior.

5.2.2 Models of Indoor Human Wayfinding

Several frameworks have been proposed to describe the indoor wayfinding process, typically breaking it down into components such as decision-making, execution, and information processing [78]. Another common approach frames wayfinding as a loop of perception, decision, and action [202]. These frameworks capture the general cognitive processes involved in wayfinding. Existing studies have developed computational models for each of these components, which will be elaborated in the following sections.

We took the perception–decision–action framework to analyze the strength and weakness of existing models, mostly ABM [65]. Indoor wayfinding models often lack realistic perception components. A common approach is to simply divide the floor plan into zones and assume that the wayfinder has access to all available information within the zone. For example, models created by Raubal, and by Maruyama and colleagues, assumed perfect sign perception within a certain distance [65,102]. Dubey and colleagues refined this approach by modeling several phases of sign perception, with increasing proximity to signs linked to a greater likelihood of correct action [109]. Gath-Morad and colleagues similarly modeled the environment as zones, with agents selecting subsequent zones based on their strength of logical association with the destination [191]. Limited models incorporated realistic and imperfect visual perception in indoor wayfinding models.

At the decision layer, a common approach in indoor wayfinding models is to use finite-state machines or flowcharts to represent high-level wayfinding strategies [102,109,191]. These approaches are generally robust, but they may omit certain local responses to complex environmental conditions (such as well-lit vs. poorly lit corridors), as well as subjective factors such as stress or fatigue that may affect strategy selection and implementation. Few studies have attempted to model problem-solving heuristics in indoor wayfinding. Gath-Morad et al. incorporated floor and central strategies into their agent-based model [193] for unaided wayfinding, but no existing model captures the interplay between wayfinding with and without signage in multi-level buildings.

At the action layer, a common approach is to model an agent's movement as transitions between discrete nodes, omitting the complexity that occurs during the transition.[65]. This method provides a succinct representation of the movement and reduces computational costs. However, it overlooks the cost of travel, perception, and uncertainty experienced between nodes. Other models represent an agent's movement as discrete locomotion, where the agent moves one step at a time [102,193]. While this approach provides more realistic movement, existing studies focus on performance metrics like total travel time, rather than enhancing the realism of on-route wayfinding behaviors. A continuously moving agent, similar to a human, could offer a more accurate estimation of sign perception and open opportunities for incorporating on-route decision-making.

It is notable that validation of indoor wayfinding models with human subjects is quite limited, which makes it difficult to assess the accuracy of their decision heuristics. For example, Gath-Morad and colleagues compared their model's output to a shortest-path agent [191], Maruyama and colleagues validated against data from three human participants [102], and Dubey and colleagues validated their model in a VR environment [109].

Looking beyond generalized indoor wayfinding models, there is another substantial body of modeling literature that focuses specifically on evacuations. These models generally feature more complex perception-decision functions but fewer high-level wayfinding strategies [106,189]. Such approaches may be suitable for the simpler wayfinding tasks involved in evacuation, which in many cases are limited to seeking the exit from a single room. In most evacuation models, the focus is on selecting the best exit to use and then determining the optimal route to that exit. As such, evacuation models tend to have a robust focus on local perception, typically including exit distance, adjacent agents, visual access, and isovist (first-person) viewpoints [42,80,89,119]. General indoor wayfinding models could benefit from considering these approaches to strengthen their perception component. The validation of evacuation models also tends to be relatively robust, as short and well-defined wayfinding tasks lend themselves more easily to empirical data-collection. While some broader, building-scale evacuation models exist, they mostly focus on analyzing multi-agent interactions and bottlenecks, and are therefore less concerned with individual factors, often using simplistic shortest-path algorithms to determine each agent's evacuation path [80,81,119].

To enhance the realism of wayfinding models, there is a growing trend towards integrating empirical data into their development. Huang and colleagues exemplify this approach by calibrating individual risk-taking parameters in their model using data from seven different evacuation experiments. These authors also validated their model's predictions against new data from three subsequent experiments [119]. Another example is Gath-Morad and colleagues' model, in which the agents' decisions are informed by the logical association parameters between the current zone and the destination; these parameters were derived from an earlier empirical study involving 24 participants [203]. Zhu and colleagues developed discrete-choice and machine learning models to predict tactical exit choices in evacuation scenarios; these models were informed by data collected from 275 participants in VR environments [42]. Similarly, Snopkova and colleagues and Juřík and colleagues integrated data from 35 participants to improve their models' performance [80,89]. This is an exciting direction in the field, as data-driven models have the potential to replace probabilistic distribution approaches and improve on deterministic behavior rules, potentially improving realism at both the micro and macro levels [67,204].

To conclude, current indoor wayfinding models can be enhanced by incorporating more realistic visual perception, modeling natural continuous movements, increasing validation with human participants, and integrating empirical data.

5.2.3 Cognitive Factors in Wayfinding Models

Including cognitive factors into the model can improve the realism of the agent behaviors and provide feedback of human factors [205,206]. Multiple studies have sought to integrate cognitive elements such as emotions, panic, stress, risk-taking, and confusion into the modeling process to improve the realism of agent behaviors [110,111,207,208]. A common strategy involves translating empirical observations into rule-based systems to determine these cognitive factors. For instance, in Raubal's model of guided indoor wayfinding in unfamiliar settings, the agent determines "go-to" affordance by checking if signage includes destination information, subsequently choosing the path with greater affordance [65]. Similarly, Maruyama's model posits that in the absence of signage at an intersection, the agent experiences disorientation and confusion [102].

In the context of evacuation, Pan and colleagues presented a model in which an agent’s stress level is influenced by perceived urgency and uncertainty, with varying stress thresholds activating distinct behavioral responses. However, the stress responses they included are purely theoretical, with no specific grounding in empirical study [110]. Similarly, Ding and colleagues described an agent model in which anxiety levels are affected by the presence of smoke and fire, but without detailing the underlying perception-cognition mechanism or the empirical basis of the simulated responses [123]. In a more detailed study on seismic evacuation, De Iuliis et al. identified four anxiety predictors for agents: predisposition to panic, personal and others' injury levels, and the presence of surrounding debris. Here, the agent's panic level is derived from a weighted linear combination, with weights indicating personal biases. A panic threshold is established to influence agent behaviors, and the study investigates the effects of varying this threshold on evacuation outcomes [111]. McCormack and Chen prescribed how various conditions—such as visibility of hazards, obstructed pathways, and the panic levels of surrounding agents—can modify an agent's panic values [209]. While these rule-based heuristics offer insights into potential psychological factors influencing agents during wayfinding, they are not based on empirical data, and generally overlook individual differences, and their applicability is limited in more complex and realistic environments.

Another approach to integrating cognitive factors is utility theory, which establishes a set of parameters that agents seek to optimize. For example, in an evacuation the utility of a path choice might influenced by factors such as its distance from hazards, proximity to exits, visual access, potential for collisions, and guidance from leaders [40,68,122,210,211]. Work by Huang and colleagues and by Gao and colleagues has combined individual risk preference parameters with utility analysis, creating a “prospect theory” that they claim offers a nuanced representation of human decision-making processes [90,119]. While the work in this area has almost exclusively focused on evacuation scenarios, it is commensurate with our interest in modeling continuous levels of path uncertainty along a route, as a means of capturing some of the underlying moment-by-moment cognitive experiences that contribute to overall wayfinding outcomes.

5.2.4 Perceived Path Uncertainty

Perceived path uncertainty is valuable to investigate both because of its relation to wayfinding success and because of its immediate impact on human experiences and wellbeing. Empirical studies have demonstrated a strong correlation between wayfinding performance and overall experience [212–214]. In most cases, higher wayfinding performance leads to a more positive and stress-free experience. By investigating wayfinding experience like perceived uncertainty, we can gain deeper insights into the underlying mechanisms that influence wayfinding performance.

Perceived uncertainty generally emerged from the lack of knowledge about forthcoming events [131,138]. We found two frameworks of perceived uncertainty. The Entropy Model of Uncertainty (EMU), proposed by Hirsh, Mar, and Peterson in 2012, was inspired by the entropy principle in information theory [4]. The model suggests perceived uncertainty will be affected by the range of perceived choice, and peak when perceived probability for each choice is equal. The EMU outlines two areas of uncertainty: (a) perceptual, which concerns sensory input, and (b) behavioral, focusing on uncertainty in the choice of actions.

Bach and Dolan introduced another useful analytical structure consisting of four cognitive phases where uncertainty can emerge: (1) interpretation of sensory input, (2) assessment of one's current state, (3) discerning transition rules, and (4) outcomes [7]. Consider an individual trying to navigate based on a faded sign. Initially, the person grapples with ambiguity related to the visual information: "Is that room 107 or 101?" This represents uncertainty stemming from ambiguous sensory input. Subsequently, in the context of wayfinding, the individual evaluates their current location, asking, "Where exactly am I now?", suggesting uncertainty about the current state. Suppose this person proceeds to an elevator and would like to go to the ground floor. The elevator buttons marked "T", "G", "1" could cause confusion about the floor numbering system because which one will lead, illustrating uncertainty in rule comprehension. If the individual then confronts two corridors that appear identical, they face uncertainty in predicting the outcome, as they need to evaluate the likelihood of each pathway leading to their intended destination. We think the perceived path uncertainty can be seen as the sum of uncertainties from these four stages.

Existing measures of perceived path uncertainty in spatial environments are limited, with most relying on self-report methods [24,215]. Besides task-level surveys, a recent study introduced a continuous measure for perceived uncertainty using the joystick method [216], where participants continuously report their perceived uncertainty by pushing a joystick. Another study aimed to decode perceived uncertainty states from bio-signals, annotating uncertainty states from first-person wayfinding videos [217]. As our goal is to develop a moment-by-moment perceived uncertainty prediction model, we utilized the joystick technique to collect data on wayfinders' perceived uncertainty.

Studies have suggested that perceived path uncertainty can have both positive and negative effects [3,4,6,9,18,131]. On one hand, it can lead to heightened information-seeking behavior and possibly more attention, curiosity, and memory consolidation of the environment [18,141]. On the other hand, however, it can contribute to frustration, anxiety, feelings of insecurity, and other negative reactions [64,216,218]. Perceived path uncertainty has also been associated with avoidance behaviors and risk-averse wayfinding strategies [140], as well as a broad deterioration in wayfinding performance [3,131]. Uncertainty emerges not only at decision-making points, but also on the routes. Wayfinders can stop [144], feel uncertain and backtrack in the middle of a long corridor if not receiving confirmatory information [216]. To investigate and control such uncertainty-driven behaviors in buildings require a model predicting moment to moment perceived path uncertainty.

5.2.5 Research Gap

Our study employs the data-driven ABM approach as previous studies. To our knowledge, no current model incorporates a data-driven method to address moment-by-moment perceived path uncertainty in routine indoor

wayfinding. Predicting on-route path uncertainty also requires improving the existing path-planning model by incorporating natural visual perception, movement components, and strategies in partially guided multi-level indoor environments. Developing such an integrated model PATH-U can provide high-resolution spatial-temporal feedback, allowing designers to identify specific wayfinding shortcomings early and iterate quickly through potential design changes, thereby improving visitors' experiences and reducing post-construction renovation costs

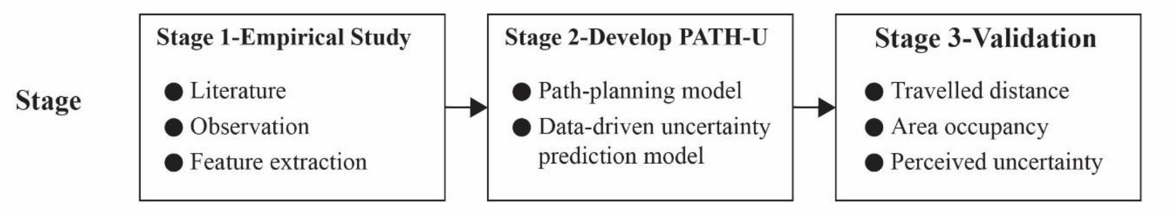
5.3 Methods

Our study aims to develop a surrogate agent for a real-world system [28,57,219]. Recent practices in data-driven ABM primarily involve three steps. The first step involves observation, literature review, and data collection to gather theoretical foundations and data for agent development. The second step involves translating empirical evidence into computational models, followed by the third step, which involves verification and validation processes [68,80,220]. This process, as suggested by one recent study [220], also adheres to the Design

Science Research (DSR) method [221]. This method emphasizes producing innovative and practical artifacts for real-world problems and includes three main components: problem identification, artifact development, and evaluation.

Our study follows a similar three-stage structure (Figure 17). In stage one, we observed human wayfinding behaviors in semi-guided, unfamiliar indoor environments. We collected their wayfinding trajectories and perceived path uncertainty data. In stage two, we modeled the behavioral rules and developed a data-driven model of perceived path uncertainty. We integrated these models to create PATH-U. Finally, we validated PATH-U by comparing the trajectories and perceived path uncertainty between simulations and human data.

Figure 17 The Process of Developing the Integrated PATH-U Model.



5.3.1 Observation Study

To empirically ground our model development, we conducted a real-world observation study with 39 participants in a complex, multi-floor university building. The sample size of 39 was chosen based on practical constraints such as time and resource availability. Additionally, each participant conducted 7 unique wayfinding tasks. Previous studies in real world wayfinding have demonstrated that a sample size of this magnitude is sufficient to detect patterns in wayfinding behavior, particularly for observation studies [102,142]. The 39 participants allowed us to collect detailed data on trajectories and perceived path uncertainty across multiple wayfinding tasks, providing robust insights into the development of our model. The participants were recruited via convenient sampling by university email list. Their ages ranged from 17 to 36 (*M* = 20.63, *SD* = 2.98). The focus on younger participants was primarily to maintain consistency in cognitive capacities and reduce variability due to age-related cognitive decline. While it is well established that wayfinding performance differs between younger and older individuals, this study aimed to first build and validate the model based on a relatively homogeneous group. Self-reported demographic information was collected, as well as statements regarding prior visit to the building in which the study took place. We measured individual differences including gender, age, and Santa Barbara Sense of Direction [180], Spatial Anxiety [179], Spatial Orientation [222]. All participants provided written informed consent to participate in the study, and our protocols were approved by the Institutional Review Board at Cornell University prior to any research activities.

During the study, each participant was asked to find seven destinations in the building. The seven tasks were arranged in a loop and assigned to participants with a randomized starting point. They were free to use the existing directional signs in the building and any other existing physical cues, but were asked not to request directions from other building occupants and not to use any electronic aids or maps that were not an integral part of the environment. (These conditions are often defined as "partially guided" or "semi-guided" wayfinding.") While seeking the destinations, participants continuously reported their perceived path uncertainty using a joystick device, with a greater extent of pressure on the joystick (in any direction) indicating greater uncertainty. This joystick-based method of continuous measurement has numerous advantages, including minimal participant task distraction and ease of analysis, and it has been validated in prior research [216]. Participants went through a training session to reduce the variability in reporting. The extent of perceived path uncertainty was continuously recorded and normalized on a scale from 0 (not uncertain) to 1 (highly uncertain). A researcher followed the participants during the wayfinding, trailing them by several meters to avoid influencing their responses and route choices. This researcher wore a body camera (GoPro Max) to document the wayfinding process (Figure 19A). After the experiment, the recorded video was used to map the participants' trajectories and synchronize them with the self-reported uncertainty data using timestamps.

The study took place across planned building renovations, during which the wayfinding signage regime and other aspects of the building were significantly altered. Some of the data (11 participants) was collected prior to these renovations, and the remainder (28 participants) was collected post-renovation. We used the post-renovation human participant data to develop our model, and then used the pre-renovation human participant data to validate the model under new conditions. In total, 273 wayfinding task trajectories (59,527 meters in total) were recorded. This data was used to develop the uncertainty prediction model and derive multi-level wayfinding heuristics.

5.3.2 Feature Extraction

We extracted potential features related to perceived path uncertainty from participants' wayfinding trajectories, conducted LASSO regression to select the most predictive and robust features (Figure 24), and fitted a multiple linear regression model to predict the perceived path uncertainty.

We extracted features relevant to wayfinding primarily from the work of Dubey [109], who categorized such information sources into five groups: signage, space, memory, crowd, and history. The “signage” category describes information gained from all types of human-made guidance materials in the environment. The “space” category includes salient environmental elements such as geometric form, lighting, obstacles, landmarks, and available pathways. “Memory” includes previous spatial knowledge of the environment or similar environments. “Crowd” describes the influence of nearby people’s behavior on wayfinding choices. “History” serves as a catch-all term for individual preferences such as the propensity for risk-taking when selecting unknown routes. Much of the recent literature in wayfinding research has adopted this framework—for example by seeking to identify how people prioritize these different categories of information in various environmental contexts, or by evaluating the different cognitive strategies associated with each category of the information [144,223,224]

Under the signage category, we extracted four features. The “Visible All Sign” was measured by adding up the total number of non-occluded signs within the isovist area (i.e., signs that the participant could read at any given time). The “Visible Helpful Sign” was the subset of visible signs that contained directional information related to the current wayfinding task. “Closest Helpful Dist” measured the distance between the agent and the closest sign with directional guidance if there was any. “Time Helpful SignSeen” measured how much time had passed since the last non-occluded, helpful sign was within the agent’s isovist area. For the spatial category, we extracted 16 metrics within the isovist representational framework, which include important aspects of how humans experience their surroundings, such as the shape of the visible area and its skewness compared to the direction of motion [225,226]. We also included the “Number of Route Choices,” measured by the number of available corridors connected to the current wayfinding decision zone.

Under the memory and history categories, previous studies have shown that participants' previous spatial knowledge of the environment (feature name "Prior Visit"), as well as objective and subjective spatial abilities such as the self-reported sense of direction (feature name "SBSOD"), mental rotation, spatial anxiety, spatial orientation, age, and gender are associated with wayfinding performance [128,142]. These variables were measured by our division of participants into "experts" vs. "novices" in relation to their prior knowledge of the building. We did not include any variable related to "crowd behavior" limited by empirical data. We also omitted personality factors beyond the spatial abilities such as risk-taking proclivity. The full list of extracted features in the current study is summarized in Table 8.

As part of extracting environmental features from the human participants' wayfinding trajectories, we created an agent in the digital model that precisely followed each participant's trajectory and simulated the participant's visual perception (Figure 18). This trajectory was sampled at 1 Hz. Based on human vision span, we defined the agent's field of view as 120 degrees [227]. The font size on the signs is 6.5mm, and an individual with 20/20 visual acuity would be able to recognize the text at around 4.5m based on Snellen Chart [228]. Therefore, we defined the agent's visual acuity as 4.5m. When the agent mimicked participants' trajectories, features in the Space category were derived using the DecodingSpaces toolbox [63].

Figure 18 An Example of an Agent Retracing a Human Participant's Trajectory to Extract Features.

5.3.3 Feature Selection

We used Lasso regression for feature selection. By introducing a penalty parameter lambda, lasso regression forces the coefficients of less important features to shrink towards zero. This effectively reduces the complexity of the model. This method was used in feature selection among larger spatial features during wayfinding [229]. The lambda was chosen with 10-fold cross validation and we chose the lambda corresponding to the minimum cross-validation error plus one standard deviation. We filtered out features with zero coefficients and selected the top one or two from each category of information sources, resulting in a total of five features.

5.3.4 Validation

After developing PATH-U, we validated the model by measuring the model's output against two baseline agents as well as novel human data from 11 participants. Both of the baseline agents made use of the A* shortest path algorithm to complete wayfinding tasks. One of the baselines added uncertainty predictions based solely on the number of route choices available at a given location (more route choices were equated to proportionally larger uncertainty); we referred to this as the "Simple Heuristic Agent". The second baseline was a shortest-path agent whose perceived path uncertainty at each location was randomly generated; this was labeled as the "Random Agent."

Table 8 Identified Possible Features that Affected Wayfinding Uncertainty

Category	Feature Name	Type	Range	Unit
Space	**Isovist spatial metrics** (16 total)	Numeric	Varies	Dimensionless
	Num Intersection (Number of available route choices)	Integer	[1, 6]	Route choice
Signage	**Visible All Sign** (Number of visible signs)	Integer	[0, 6]	Sign

	Visible Helpful Sign (Number of visible helpful signs)	Integer	[0, 5]	Sign
	Closest Helpful Dist (Distance to the closest helpful sign)	Numeric	[0, 4.5]	Meter
	Time Helpful SignSeen (Elapsed time since seeing the last helpful sign)	Numeric	[0, 3534]	Frame Count
Memory	**Prior Visit**	Categorical	{1, 0}	Yes or No
History	**SBSOD**	Numeric	[1, 7]	Score
	Spatial anxiety	Numeric	[1, 5]	Score
	Spatial orientation	Numeric	[0, 180]	Angle
	Mental Rotation	Integer	[0, 24]	Score
	Age	Numeric	[0, 72]	Years
	Gender	Categorical	{1, 0}	M or FM

5.3.5 Validation Metrics

We used travelled distance of each task as the metric for validating the path-planning model in PATH-U. Travelled distance provides a aggregated evaluation for wayfinding performance, and well accepted in existing wayfinding simulations [191,192,220]. As for validating the uncertainty prediction of the integrated model. We used two fine-grained metrics. First, we created kernel density maps of both human and agent's Area Occupancy (Figure 25) and Perceived path uncertainty (Figure 26), and qualitatively comparing the spatial distribution of uncertainty levels, averaged across all participants or agents. Second, we make a quantitative comparison between these maps. we used the Dynamic Time Warping (DTW) algorithm, which measures the similarity between two temporal sequences that may or may not have equal lengths [230].

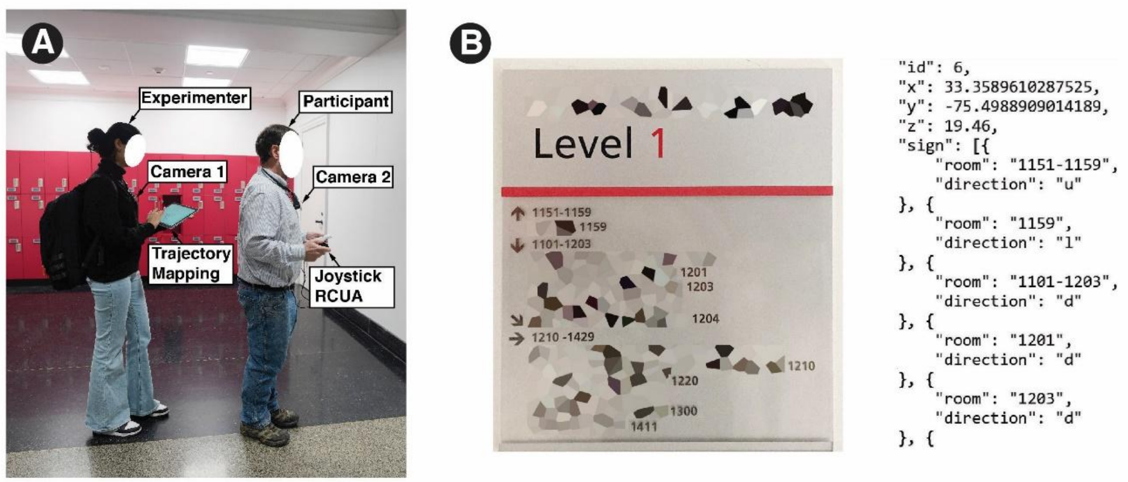
We introduced two baseline agents to better illustrate the performance of our model. One baseline agent is the heuristic agent whose perceived path uncertainty solely depend on the number of route choice. Another baseline agent was the random agent whose perceived path uncertainty at each timestep was randomly generated. We compared the metrics of PATH-U, and those baseline agents against human data in the validation set.

5.3.6 Validation Setup

As discussed in the Methods, the validation data was collected in the same building and using the same wayfinding tasks as the model-training study, but under a different signage regime and with a different group of 11 participants (77 wayfinding tasks). The data-collection process for these participants was identical to that used in the model-training data.

We simulated 11 agents in PATH-U and in each of the other baseline models to match the 11 human participants in the validation study. In the PATH-U simulation, these agents were assigned the same values of selected features as their corresponding human counterparts such as SBSOD scores (model variable $X4$) and prior visit (model variable $X5$). Stochastic elements were introduced by varying agent speed (1.1 to 1.2 meters per second), field of view radius (9.9 to 10 meters), and view angle (70 to 130 degrees). The selected speed range is based on established norms for average human walking speeds under varying external conditions, such as density and corridor widths [231]. Speed is dynamically reduced in dense environments and narrow corridors to better reflect real-world movement constraints. The variation in view angle was implemented to realistically model the natural neck movements observed during our observation study. This approach enables agents to more accurately perceive and respond to environmental cues, such as signage, by dynamically adjusting their line of sight based on the text height and width of the signage. These adjustments capture the inherent variability in human behavior, ensuring that the simulation replicates realistic movement patterns and perception.

Figure 19 (A) Setting of the Wayfinding Experiment and (B) One Example of the Directional Signs and Its JSON Format in the Building



```
"id": 6,
"x": 33.3589610287525,
"y": -75.4988909014189,
"z": 19.46,
"sign": [{
    "room": "1151-1159",
    "direction": "u"
}, {
    "room": "1159",
    "direction": "l"
}, {
    "room": "1101-1203",
    "direction": "d"
}, {
    "room": "1201",
    "direction": "d"
}, {
    "room": "1203",
    "direction": "d"
}, {
```

However, we recognize that these parameters may not fully represent the complete range of human heterogeneity. Moving forward, we plan to refine these variables by incorporating data collected from participants, allowing us to simulate a broader spectrum of behaviors and thereby enhance the overall accuracy and realism of our simulations. Comparisons were made between each corresponding agent and human, and the results were then aggregated at the task level. Those data were processed to generate travelled distance per task, area occupancy map, kernel density map, and DTW by zones.

5.4 Developing the PATH-U

PATH-U was designed as an integrated model, combining a path-planning model with a data-driven uncertainty prediction model for multi-floor, partially-guided wayfinding tasks conducted in unfamiliar environments (Figure 20). The path-planning model is developed based on the literature and observation in our empirical study, which includes the environmental representation, human visual perception, natural movement, short-term memory, and a finite state machine governing high-level wayfinding strategies and local route choices. The data-driven moment-by-moment route uncertainty prediction model is our novel contribution, grounded in the findings of our observational study.

5.4.1 The Path Planning Model

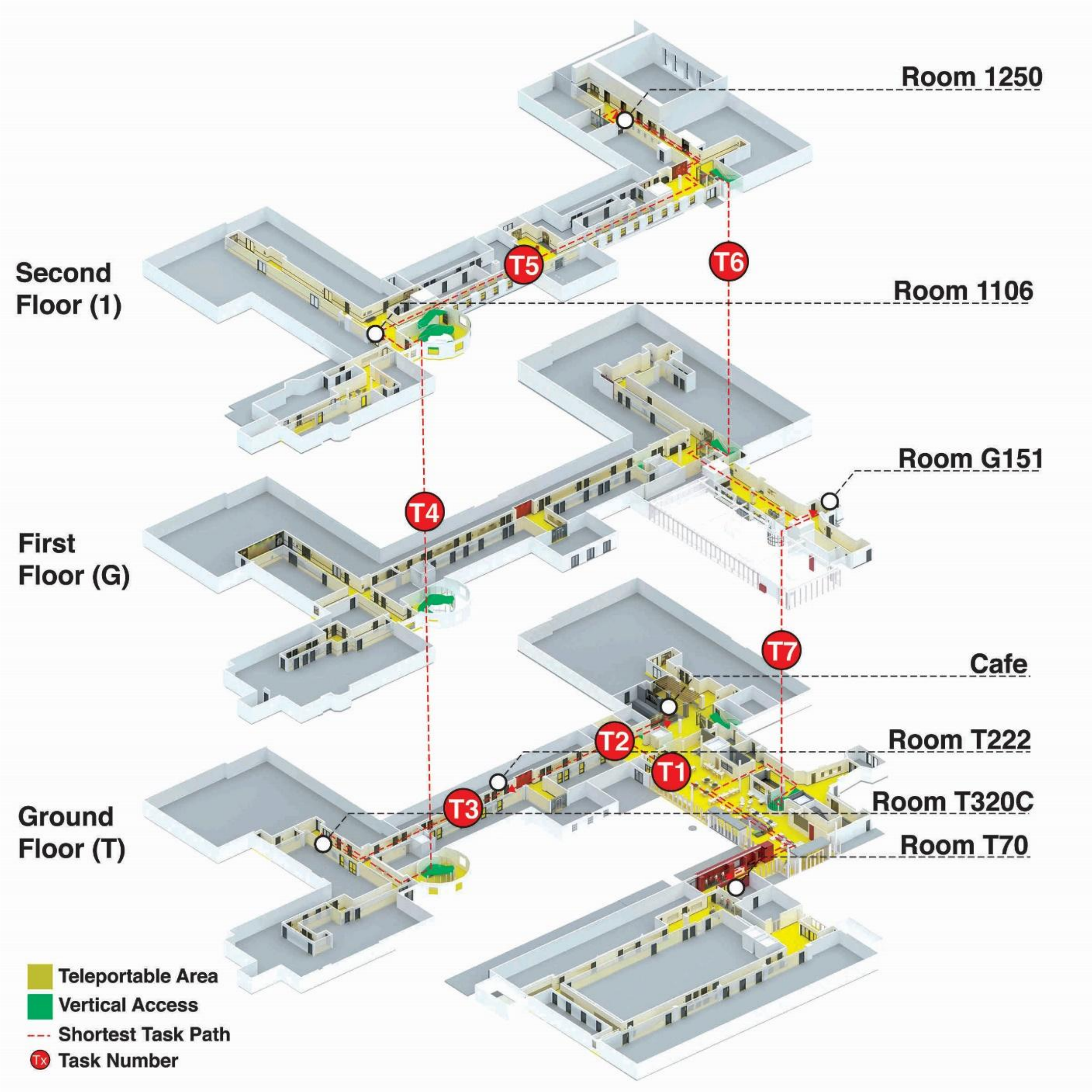
The path-planning model includes the environmental modeling and multiple modules, such as visual perception, natural movement, short-term memory, and a finite state machine governing high-level wayfinding strategies and local route choices. We present the pseudo code for the path-planning model in Figure 22.

5.4.2 Modeling the Physical Environment

The basic environmental model consists of a 3D building imported and augmented (with added stairs between floors) in the Unity 3D engine. In the default Unity3D engine, the navigational area is modeled as a continuous mesh, enabling realistic movement and visual perception in a 3D environment. However, we implemented several enhancements on top of this basic model. In our proposed framework, the 3D environment's navigable surface is divided into an array of 1 m by 1 m rectangular grid cells, which approximates the average step length and size of an adult. This virtual grid map serves as a reference for an agent's location and allows us to match agents’ step size with the human participants in later VR studies. We surveyed real-world signs providing directional information and digitized them into a structured JSON format. Individual directional signs were identified in the simulation by their attributes and a list of relevant goal locations (Figure 19B). We created decision-making zones and nodes where participants had to make key route choices, forming the graph structure for the building and enabling us to model local decision-making behaviors based on signs [232]. Each decision-making node has a prescribed zone that triggers the agent’s decision-making process, and sub-nodes allowing agents to move towards particular routes (Figure 21).

A sign is regarded as visible to an agent when it is within the agent’s field of view and there is no occlusion, as determined by a dynamic visibility check [109]. The path-planning model’s wayfinding environment is implemented using a navigation graph, where each intersection (i.e., decision point) acts as a node, with paths (corridors or hallways) connecting two nodes.

Figure 20 The Map of Seven Wayfinding Tasks (during Actual Data-collection the Researcher Trailed the Participant by Several Meters)



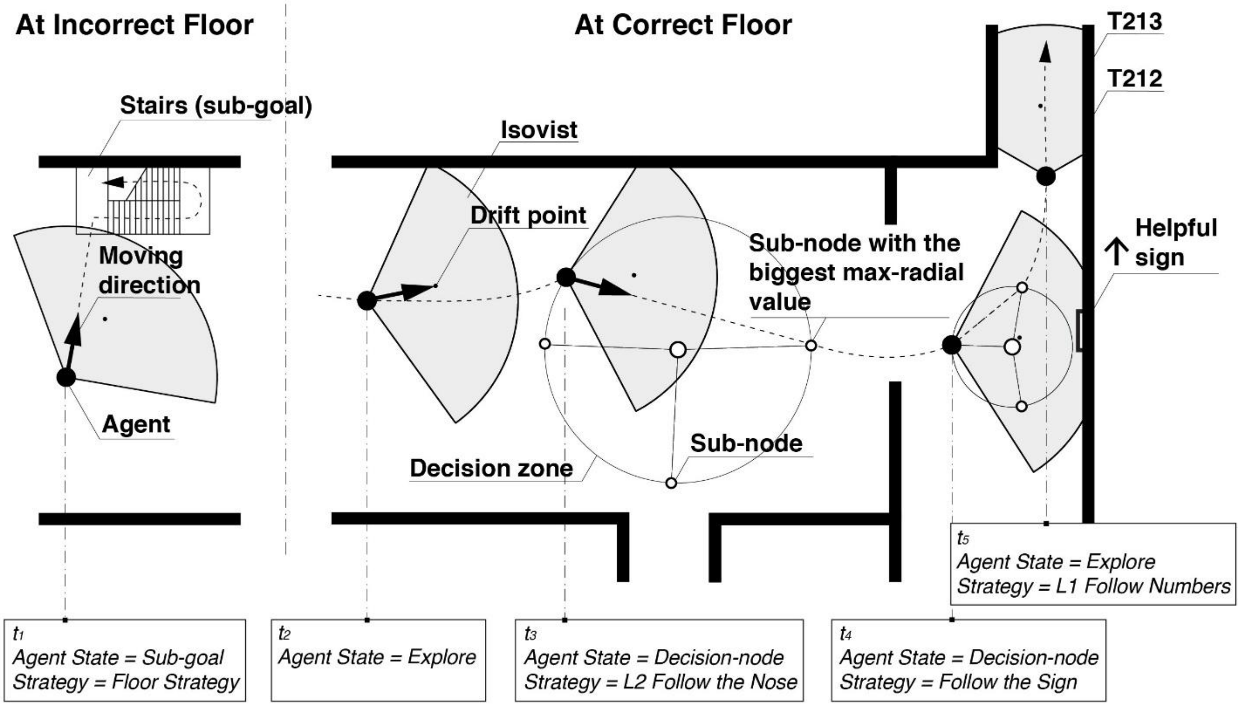
5.4.3 Modeling the Visual Perception

To realistically simulate visual-based interactions between agents and their environment, we emphasize evaluating the visibility of directional signs and considering dynamic occlusions [233]. The dynamic sign visibility check is a runtime visibility test that evaluates dynamic occlusions using raycasting function in Unity. When an agent enters the Visual Coverage Area (VCA) of a sign, the system performs a visibility check to detect any occlusions caused by other agents or physical barriers within the agent's visual field. Five rays are cast from the agent's eye position, towards the center and four corners of the sign. If at least three of the five rays hit the sign unobstructed, the sign is considered visible. This perceptual-based agent-signage interaction system was motivated by prior work [109]. To account for typical human neck rotation when searching for nearby environmental cues, our model defines the agents' horizontal field of view as 120 degrees [234]. The full interior height, from floor to ceiling, is assumed to be visible within this field of view. The distance from which signs can be read (isovist radius) is set to 10 meters. These parameters can be adjusted by the model's users as needed, for example, in environments with very large or very small signs. Our work did not consider the specific wayfinding needs of the visually impaired, which is a crucial topic but is beyond the scope of the current research.

5.4.4 Modeling the Natural Movement

The model aims to simulate a human's natural wayfinding movement pattern without a predetermined or optimized path, reflecting a visitor's exploration behavior in an indoor environment with imperfect information. We employed a partial isovist approach, a constrained visible area limited by the 120-degree field of view and the surrounding walls and objects. When

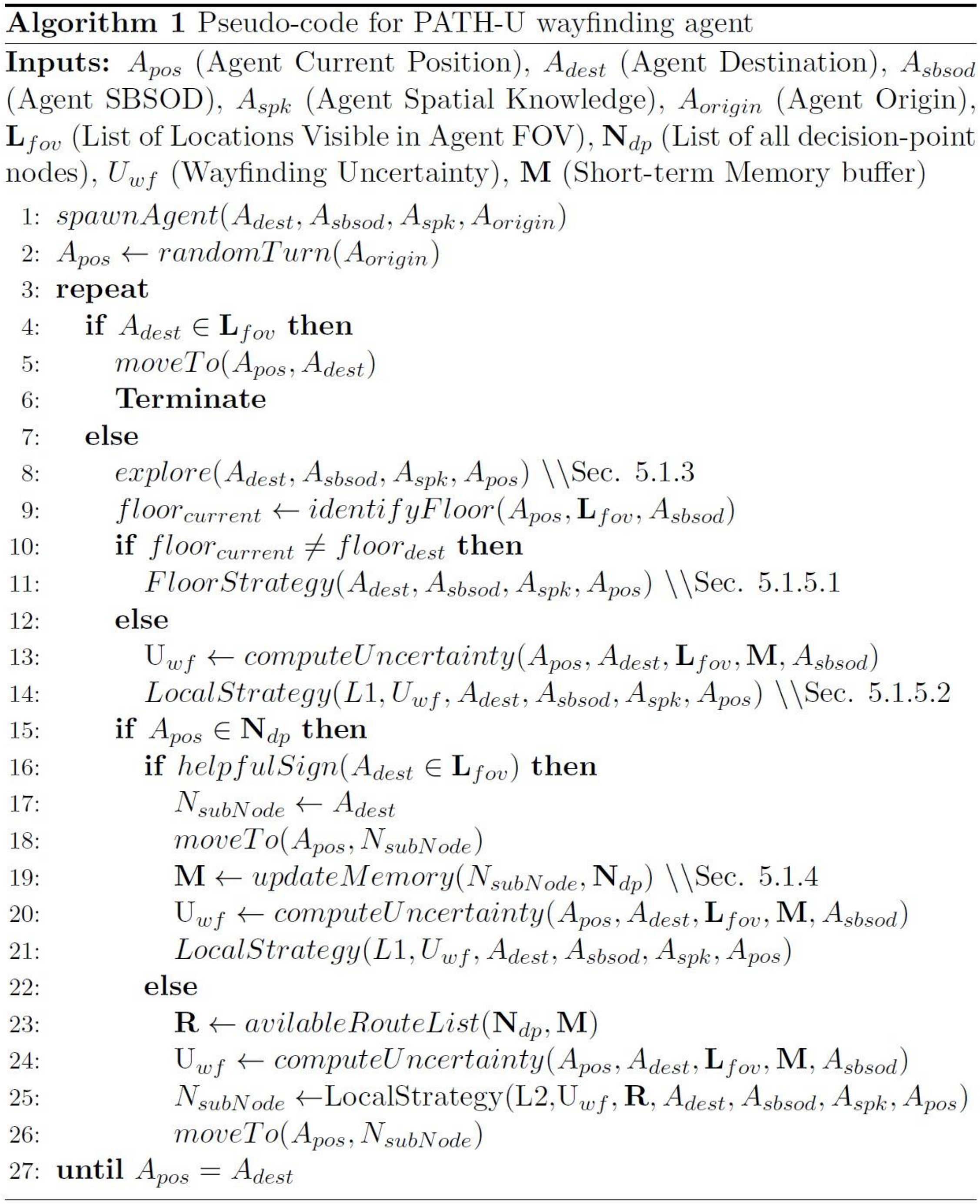
Figure 21 Visualization of An Agent's Moving Directions Under Different States



the agent was outside the decision-making zone (under "Explore" state), we identified a "drift" point at the centroid of the agent's field of view, toward which the agent moves by default. The centroid is the mathematical center point of the visible space, determined by the contours of the visible area (Figure 21). This process of identifying the isovist space and centroid is continuous, dynamically adjusting the drift position as the agent moves.

When the agent was inside the decision-making zone, or has specific sub-goals or destinations in sight, the agent conducts goal-oriented movement towards those destinations, as defined by a shortest-path algorithm.

Figure 22 Pseudo-code for the PATH-U agent



Algorithm 1 Pseudo-code for PATH-U wayfinding agent

Inputs: A_{pos} (Agent Current Position), A_{dest} (Agent Destination), A_{sbsod} (Agent SBSOD), A_{spk} (Agent Spatial Knowledge), A_{origin} (Agent Origin), $\mathbf{L}_{fov}$ (List of Locations Visible in Agent FOV), $\mathbf{N}_{dp}$ (List of all decision-point nodes), U_{wf} (Wayfinding Uncertainty), $\mathbf{M}$ (Short-term Memory buffer)

```
$spawnAgent(A_{dest}, A_{sbsod}, A_{spk}, A_{origin})$
$A_{pos} \leftarrow randomTurn(A_{origin})$
repeat
    if $A_{dest} \in \mathbf{L}_{fov}$ then
        $moveTo(A_{pos}, A_{dest})$
        Terminate
    else
        $explore(A_{dest}, A_{sbsod}, A_{spk}, A_{pos})$ \\Sec. 5.1.3
        $floor_{current} \leftarrow identifyFloor(A_{pos}, \mathbf{L}_{fov}, A_{sbsod})$
        if $floor_{current} \neq floor_{dest}$ then
            $FloorStrategy(A_{dest}, A_{sbsod}, A_{spk}, A_{pos})$ \\Sec. 5.1.5.1
        else
            $\mathrm{U}_{wf} \leftarrow computeUncertainty(A_{pos}, A_{dest}, \mathbf{L}_{fov}, \mathbf{M}, A_{sbsod})$
            $LocalStrategy(L1, U_{wf}, A_{dest}, A_{sbsod}, A_{spk}, A_{pos})$ \\Sec. 5.1.5.2
        if $A_{pos} \in \mathbf{N}_{dp}$ then
            if $helpfulSign(A_{dest} \in \mathbf{L}_{fov})$ then
                $N_{subNode} \leftarrow A_{dest}$
                $moveTo(A_{pos}, N_{subNode})$
                $\mathbf{M} \leftarrow updateMemory(N_{subNode}, \mathbf{N}_{dp})$ \\Sec. 5.1.4
                $\mathrm{U}_{wf} \leftarrow computeUncertainty(A_{pos}, A_{dest}, \mathbf{L}_{fov}, \mathbf{M}, A_{sbsod})$
                $LocalStrategy(L1, U_{wf}, A_{dest}, A_{sbsod}, A_{spk}, A_{pos})$
            else
                $\mathbf{R} \leftarrow avilableRouteList(\mathbf{N}_{dp}, \mathbf{M})$
                $\mathrm{U}_{wf} \leftarrow computeUncertainty(A_{pos}, A_{dest}, \mathbf{L}_{fov}, \mathbf{M}, A_{sbsod})$
                $N_{subNode} \leftarrow \mathrm{LocalStrategy}(\mathrm{L2}, \mathrm{U}_{wf}, \mathbf{R}, A_{dest}, A_{sbsod}, A_{spk}, A_{pos})$
                $moveTo(A_{pos}, N_{subNode})$
until $A_{pos} = A_{dest}$
```

5.4.5 Modeling the Short-Term Memory

We implemented a simple short-term memory model for the agent, allowing it to recall the route choices made at each traversed node throughout the entire wayfinding task. This model simulates human-like decision-making in route selection using memory. For instance, if the agent encounters a decision node and initially chooses a left turn that does not lead to the correct route, it will remember this outcome. Upon revisiting the same decision node during the wayfinding journey, the agent will avoid choosing the left turn again and opt for a different route from the available options. The newly selected route is then added to the agent's memory specific to that decision point.

5.4.6 Modeling the Wayfinding Strategies

Modeling the path-planning model includes modeling both local and global wayfinding strategies. At the local level, we model the agent’s decisions at an intersection or on a route. At the global level, we model the high-level problem-solving workflow of multi-level semi-guided wayfinding tasks using a finite state machine.

5.4.6.1 Global Wayfinding Strategy

At the global strategy level, our agent will first proceed to the correct floor of the building, by seeking the closest floor transition point (stairwell, elevator, etc.) irrespective of the horizontal location of the destination room. This is referred as **Floor Strategy**, a well-established wayfinding heuristic that reflects human behavior [144]. After arriving at the correct floor, the agent will then prioritize signs indicating access to the destination. If there is a relevant, non-occluded sign in visual range, then the agent will follow the route indicated by that sign. If such signs are missing or occluded, then the agent will enact local wayfinding strategies until a relevant sign is seen or the destination is reached.

Figure 23 presents the global structure of the proposed agent-based model. We modeled the agents’ behavior as a finite state machine, meaning that each agent can be in exactly one of a finite number of states at any given time. The agent can change from one state to another in response to environmental input. The proposed model includes four main agent states:

Explore: In this state, the agent explores the environment, exhibiting a moderately high degree of drift, seeking for directional cues and using its natural movement.

Sub-goal: In this state, the agent is assigned a temporary sub-goal of finding a floor transition (staircase/escalator/lift) and performing a shift in floor level. This state occurs when the agent has determined that the destination is not on the current floor.

Decision-node: In this state, the agent is inside a decision zone and must choose between branching available routes. The choice of route depends on information available in the environment. If there is a helpful sign in visual range, then the agent selects the directional information perceived from that helpful sign. In the absence of any helpful sign, the agent selects the route with the longest visual sight range (i.e., line of sight). If multiple unknown routes have the same sight range, then the agent will select randomly between the routes which were not taken previously. The agent maintains a short-term memory using a navigation graph of routes taken during the wayfinding task.

Execute: In this state, agent navigates directly toward the identified destination.

5.4.6.2 Local Wayfinding Strategies

These local strategies include, first, following continuously marked room numbers (Local Strategy L1). For example, if the agent is trying to find room 325 and sees rooms 312, 313, and 314, it continues to move in the direction. If the room numbers are not getting numerically closer

Figure 23 Finite State Machine Diagram of Agents' Wayfinding Strategies

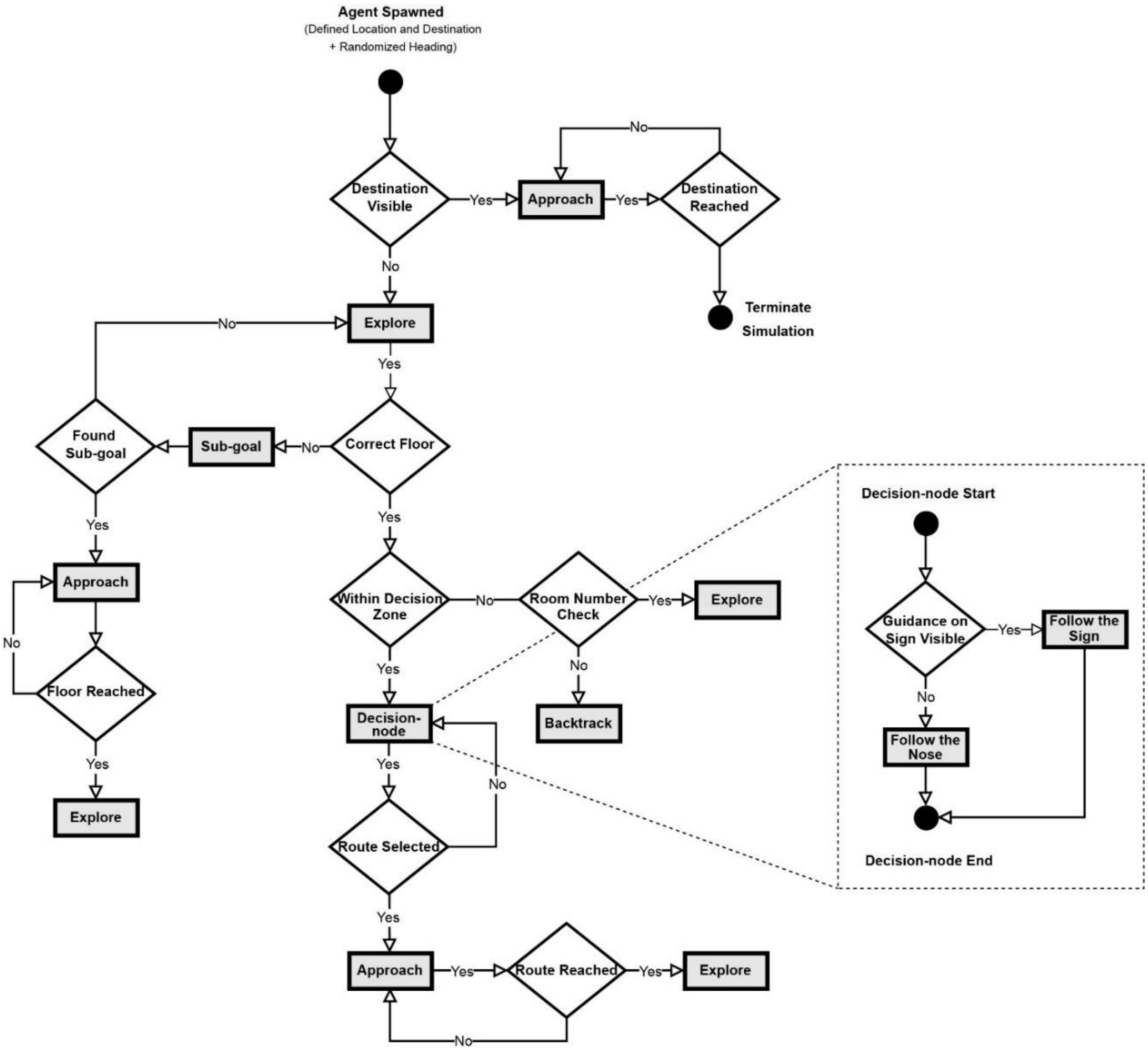
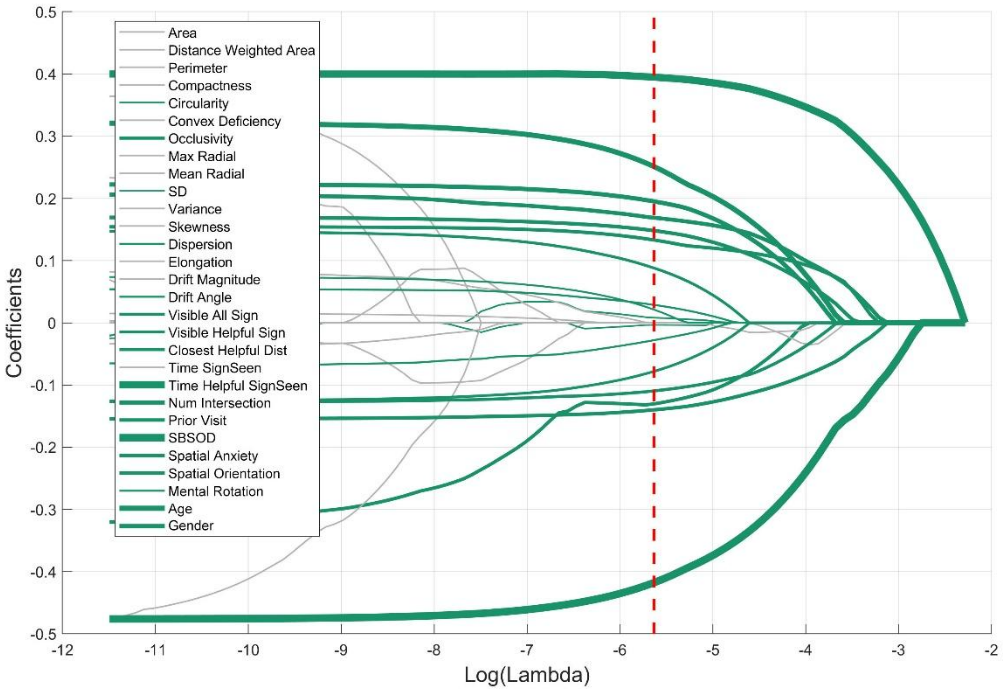


Figure 24 Lasso Path Visualizing the Strength of Coefficients of Different Features. Note: red vertical line indicates lambda strength such that the model's cross-validated error is within one standard error of the minimum cross-validated error



to the destination room, the agent backtracks. Second, if there is no clear sequence of room numbers, then the agent will adopt the **local strategy L2** of "**following your nose**" by continuing in as straight a route as possible with minimal angular deviations (in this context, based on prior usage in the wayfinding literature, the phrase "follow your nose" is interpreted to mean moving straight ahead). These algorithmic strategies are all grounded in prior empirical study of how humans approach wayfinding in unfamiliar indoor environments [126,235,236].

5.4.7 The Uncertainty Prediction Model

The results yielded several interesting insights. We found that none of the isovist spatial metrics had a strong impact on participants' perceived path uncertainty, which suggests that certain architectural features (such as the expansiveness of the visible space) were not an important consideration in comparison to other evaluated factors. We did find, however, that

“Num Intersection” had a moderately strong effect on uncertainty. Regarding signage features, we found that the “Time Helpful SignSeen” were quite influential on uncertainty. In the memory and history categories, the “SBSOD” was a very strong predictor of uncertainty, with “Age” and “Gender” having moderate impacts. “Prior Visit” has a moderate impact on perceived uncertainty.

Ultimately, we selected five key features to use in the uncertainty prediction model. These included the number of route choices available ($X1$), the number of visible helpful signs ($X2$), the elapsed time since seeing the last helpful sign ($X3$), the agent’s sense of direction as SBSOD score ($X4$), and the agent’s prior knowledge of the environment on a range of 0 (unfamiliar) to 1 (familiar) ($X5$). The first three parameters are continuous features of the agents’ interactions with the environment. The last two parameters are individual features that can be customized to create agent variability or to reflect a human participant sample. Based on our empirical data we calculated regression coefficients, labeled $\beta 1$ through $\beta 5$ respectively for each included variable. These coefficients represent the observed effect strengths for each item on the perceived path uncertainty (Table 9). After adding the regression model’s intercept $\beta 0$, the calculated uncertainty of an agent ∇ during wayfinding is shown in Equation 3. Most of the predictors were significant. The prior visit was marginally significant but we decided to keep it as it’s the only feature we included in the “memory” category. The marginal r-squared for the model was 0.196, and the conditional r-squared was 0.388. Though our r-squared was not impressive but acceptable due to the inherent variability of human behavior data. Since most predictors were significant, we think the model provides insights despite explaining a limited portion of the variance.

$$\nabla = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \qquad (3)$$

Table 9 Parameters of the Multiple Linear Regression Model

	Coefficient	**Standard Error**	***t***	***p***
Intercept	$6.046 * 10^{-1}$	$1.575 * 10^{-1}$	3.838	0.0007
Num Intersection (X_1)	$-4.902 * 10^{-1}$	$2.090 * 10^{-3}$	-23.459	0.0001
Visible Helpful Sign ($X2$)	$3.063 * 10^{-1}$	$5.723 * 10^{-4}$	53.522	<0.0001
Time Helpful SignSeen (X_3)	$2.436 * 10^{-1}$	$2.457 * 10^{-6}$	99.150	<0.0001
SBSOD (X_4)	$-1.030 * 10^{-1}$	$3.888 * 10^{-2}$	-2.646	0.0138
Prior Visit (X_5)	$-1.462 * 10^{-1}$	$8.270 * 10^{-2}$	-1.768	0.0892

Figure 25 Kernel Density Map of Area Occupancy between Human and PATH-U Agents

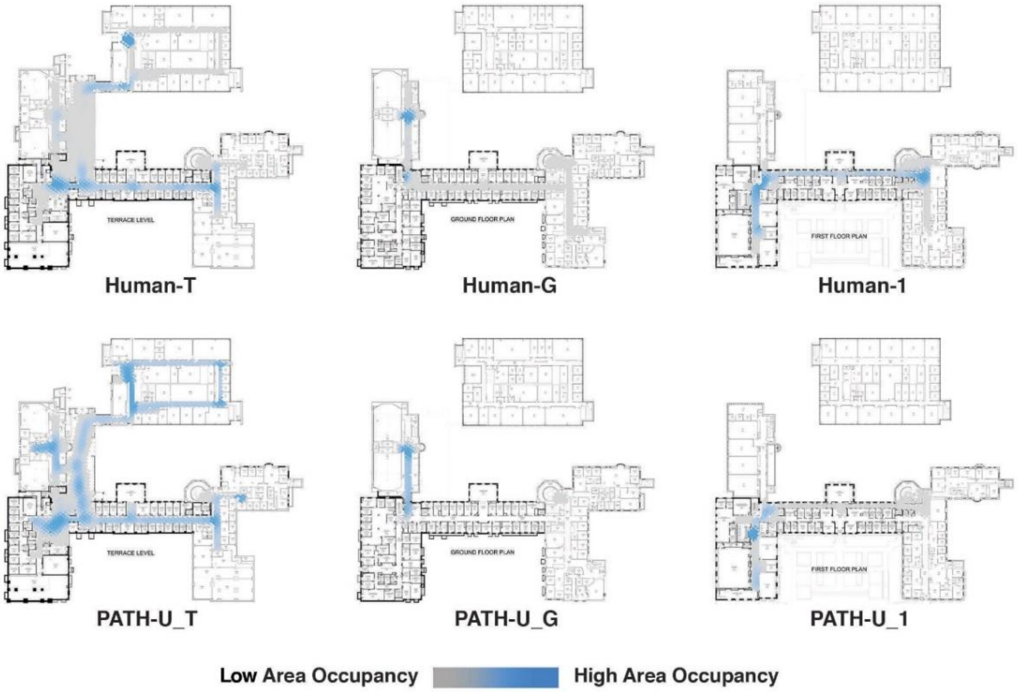


Figure 26 Kernel Density Map of Perceived path uncertainty by Human Participants, PATH-U Agent, a Simple Heuristic Agent, and a Random Agent, Across All Wayfinding Tasks (T, G, and 1 Refer to the Building Floors)

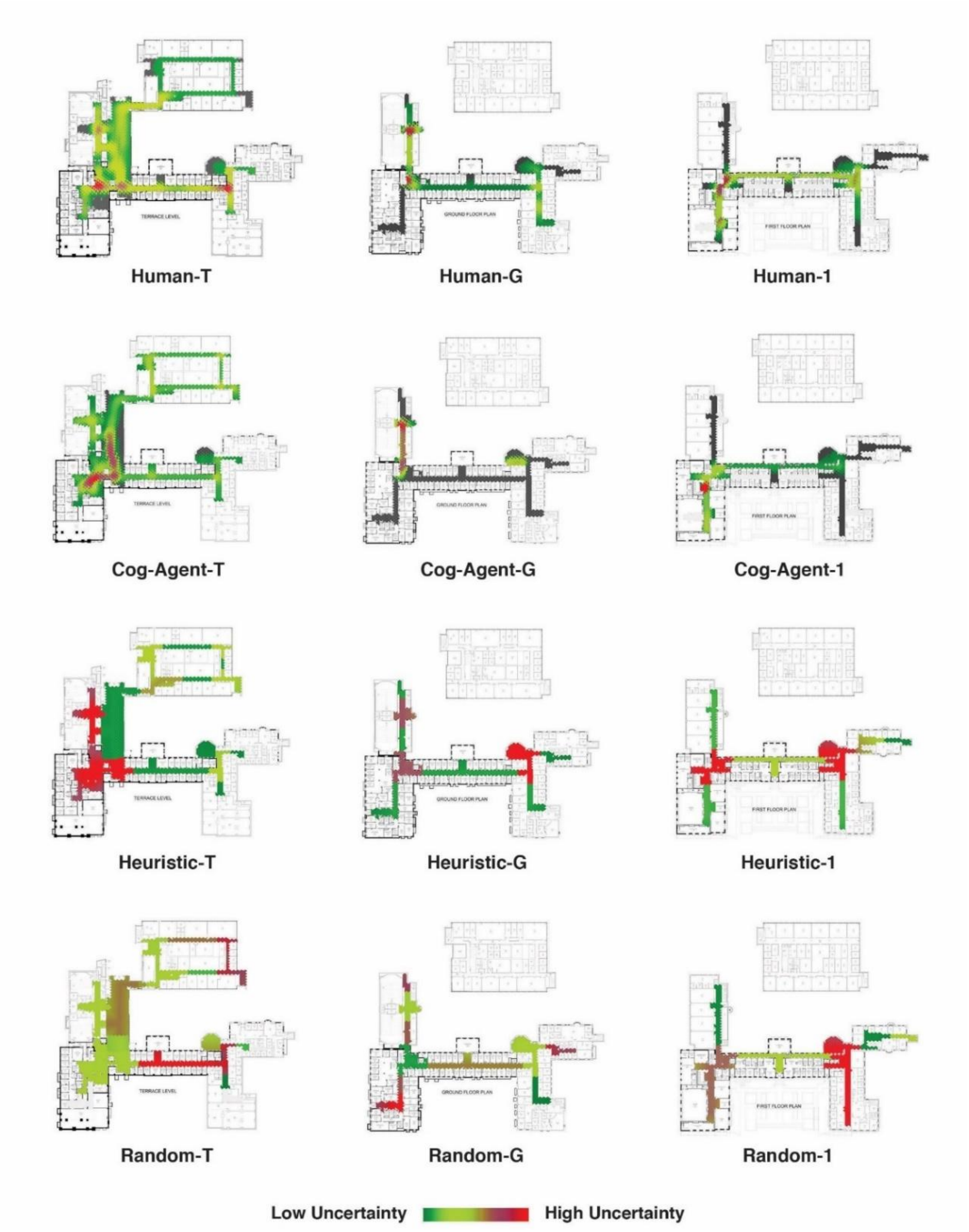
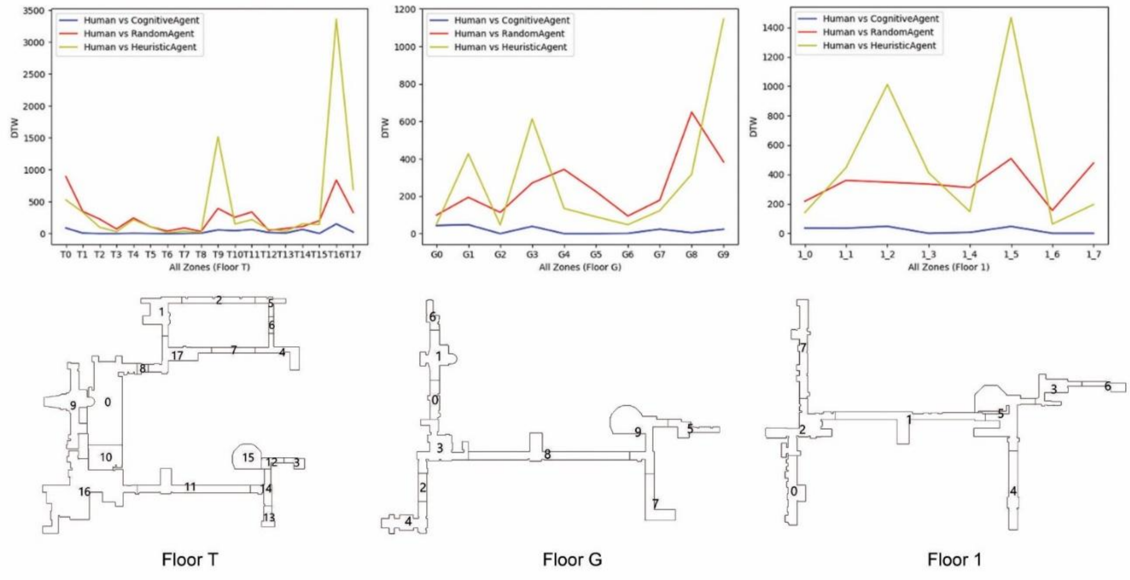


Figure 27 Dynamic Time Warping Comparison of Human Perceived Path Uncertainty vs. the PATH-U Agent, a Simple Heuristic Agent, and a Random Agent, for Each of the Three Floor Levels (Higher DTW Scores Indicate Reduced Similarity)



5.5 Validation Results

5.5.1 Results for Perceived Path Uncertainty

The spatial distribution of perceived path uncertainty was closely similar between PATH-U and human participants across all wayfinding tasks. This similarly to the human data was not observed in the Simple Heuristic Agent and the Random Agent. Figure 26 shows the kernel density maps displaying these outcomes as a visual pattern.

The DTW metric provides a more robust and quantitative means of comparing the uncertainty distribution. This analysis indicates a very close similarity between the novel human data and the predictions of PATH-U, with DTW deviation close to zero across most areas of the building and never rising above 150. In comparison, deviations between the human participants and the Simple Heuristic Agent were consistently over 200 and often spiked to 1,000 or more in zones with more intersections, such as zones T9, T16, G1, G3, G9, and 1_5. Additionally, the heuristic agent's estimates showed deviations in long-corridor zones, such as G8 and 1_1. (Figure 27).

A close examination of the DTW data revealed that PATH-U was particularly effective (closely matching human-reported uncertainty) when it came to accurately identifying high-uncertainty locations. This is an exciting result since one of the simulation tool’s most important goals is to assist designers in locating “problem spots.” However, PATH-U tended to slightly overestimate the perceived path uncertainty in some areas, particularly large open spaces without signs. It is likely that in those areas the human participants were aided by landmarks and other salient visual cues that the model overlooked. This could potentially result in “false alarms” by bringing locations to designers’ attention that did not actually need improvement.

5.5.2 Results for Travelled Distance

The overall area occupancy between PATH-U and humans is similar (Figure 25). The results of this comparison varied greatly among the different wayfinding tasks (Figure 28 and Table 10). We found that the travel distance of the PATH-U agents was most similar to that of humans in wayfinding tasks 3, 5, and 6. In these tasks, the A* agent’s travel distance was also similar to the humans and the uncertainty-based agent, albeit slightly shorter. These tasks had relatively more signs, making it easier for both agents and humans to recover from incorrect choices at intersections without signs.

In tasks 1, 2, and 7, our PATH-U agent took a much longer path than either the humans or the A* agent. Those tasks had sparse sign coverage We observed that both the agents and the humans took more wrong turns in these tasks; however, the humans recovered more quickly, frequently backtracking after moving only a short distance down an incorrect path. This could be explained by the humans picking up on broader environmental cues not included in the model, which caused them to realize they were headed in an unpromising direction. PATH-U, in contrast, continued to drift for much longer distances. The local “follow-your-nose” heuristic prompted the PATH-U agents to forge ahead in conditions of uncertainty, which did not consistently align with the human behavior of frequent backtracking.

Task 4 is the single case in which humans traveled much greater distances, while PATH-U was more similar to the A* shortest-path algorithm. In this task, we noted that PATH-U consistently outperformed the humans at a single no-sign intersection where the quickest route was to continue straight ahead. The forward route led to an obscured staircase that quickly accessed the correct floor. Most of the human participants were diverted from the shortest route at this intersection, detouring to a distant staircase that was visible at the end of a lengthy side-corridor. PATH-U, in contrast, again took the “follow your nose” approach in continuing forward. This outcome discrepancy can therefore also be attributed to the human wayfinders relying on more detailed perceptual information that the model did not notice, although in this case the observation of the distant staircases let the human wayfinders astray.

A close examination of the distance-traveled data revealed additional insights from outlier agents. In Task 2, one of the eleven PATH-U agents took a wrong turn and entered an area without signs, only returning after exploring the entire area in vain (Figure 29). This significantly affected the overall PATH-U averages for that task. In Tasks 3 and 7, certain areas caused some agents to loop, repeatedly revisiting the same spots until they escaped the loop by making a correct choice by chance. Interestingly, we noticed similar looping behavior in outlier human participants. These individuals made key mistakes such as overlooking an available turn, which lead them to perceive an area as unpromising and to waste a great deal of time going back and forth to other incorrect routes. This looping behavior continued until the participant eventually changed their belief and saw a new option in the previously visited environment. However, humans consistently escaped their loops faster than the PATH-U agents, likely due to a more sophisticated memory function.

Our results suggest the stochastic behavior in the model. The variability in view angle can lead to the agent perceiving different signs due to changes in the field of view, introducing a stochastic behavior. Additionally, the randomization of the field of view size affects the drift value, altering the agent's natural movement vector. This variation can cause the agent to approach different decision points, especially when they are in close proximity, subsequently guiding the agent towards different sub-goal nodes and resulting in varied behavior. This stochastic nature is crucial for capturing the nuances of navigation in dynamic environments which the proposed model exhibits.

Figure 28 Average Distance Traveled by Human Participants, PATH-U Agents, and the A Shortest-path Agent*

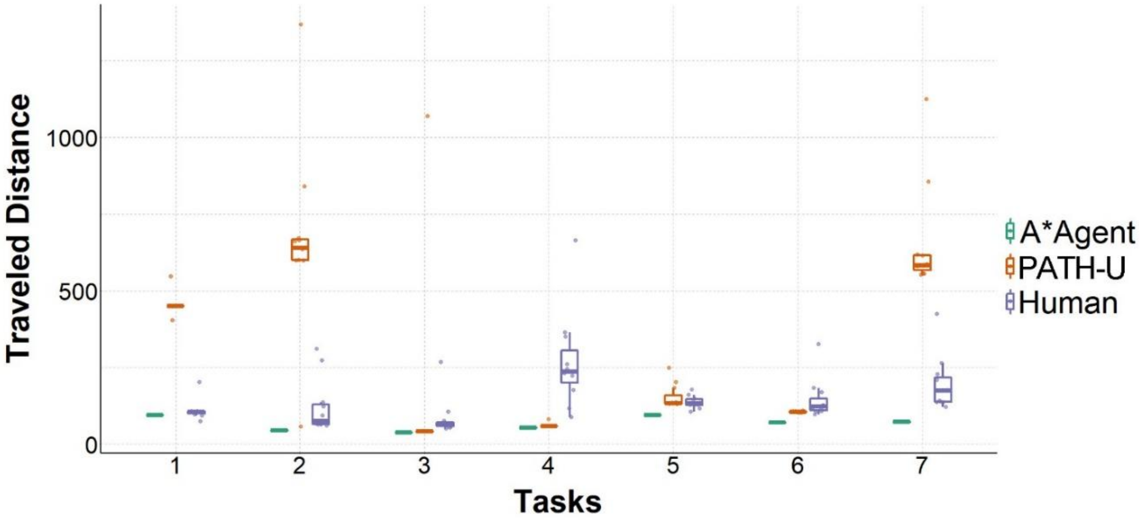


Table 10 Average Travelled Distance of Human, PATH-U, and A Agent.*

Task ID	PATH-U	Human Participants	A*Agent
1	454.75	116.78	95.23
2	666.53	121.02	44.12
3	135.52	84.03	37.64
4	61.16	271.55	54.18
5	154.01	136.71	94.41
6	105.01	145.14	70.34
7	655.05	195.06	72.16

Overall, the distance travelled by humans tended to be closer to our PATH-U agent compared with the shortest-path agents, but these differences varied greatly across different tasks, which have different interactions among signs, layout, spatial cues, and route-seeking heuristics.

5.6 Discussions

Compared to existing models of simulating wayfinding route choice and strategies [30,102,193,237], we improved the simulation's realism by incorporating short-term memory, sign perception with dynamic occlusions, and wayfinding heuristics. We also incorporated moment-by-moment predictions of perceived path uncertainty into the wayfinding simulation to help identify specific problem spots on the floor plan. Compared to a few previous models that identified problematic locations solely based on a lack of signs [65,102], our PATH-U agent considered uncertainty based on sequential and complex interactions among signs, memory, and the available route choices, and grounded these assessments on data from human participants. Our study is part of a larger movement in the field toward integrating robust empirical data about human behavior into building occupant simulation models [8,13,89]. The study demonstrates how this approach can produce more realistic agent behaviors and more detailed feedback on building designs.

The results of our empirical research were in broad alignment with previous studies in the sense that the greatest perceived path uncertainty was found when the wayfinders approached branching routes with insufficient information [58,85]. “On-route” uncertainty, which arises during the course of carrying out a previous path decision, was found to be prevalent (see Supplemental Material, Figure S3). On-route uncertainty continued to rise gradually over time when no new directional signs were seen. The greatest uncertainty occurred when participants arrived at an unmarked intersection and had not recently seen a directional sign, which often caused them to question their path and backtrack.

While the validation study showed that the PATH-U agent was effective at predicting perceived path uncertainty, it occassionally produced “false positives” in the sense of overestimating uncertainty in large open spaces with limited signage. This can be attributed to the human wayfinders drawing from diverse subtle environmental cues (lighting conditions, landmarks, crowd movement, etc.) that were not included in the model. We also found that the route choices of PATH-U significantly diverged from those of human participants underenvironmental conditions without the destination or guidance (Task 1, 2, 7). This was also likely due to the model ignoring environmental cues that the humans were aware of, for example by continuing to explore unpromising routes long after the human participants had given up and backtracked. It is likely that such discrepancies could be reduced by revising the model to limit agents’ tendency to drift toward open space and “follow your nose” (keep moving forward) in conditions of uncertainty, and replacing these behaviors with heightened information-seeking or backtracking as uncertainty rises.

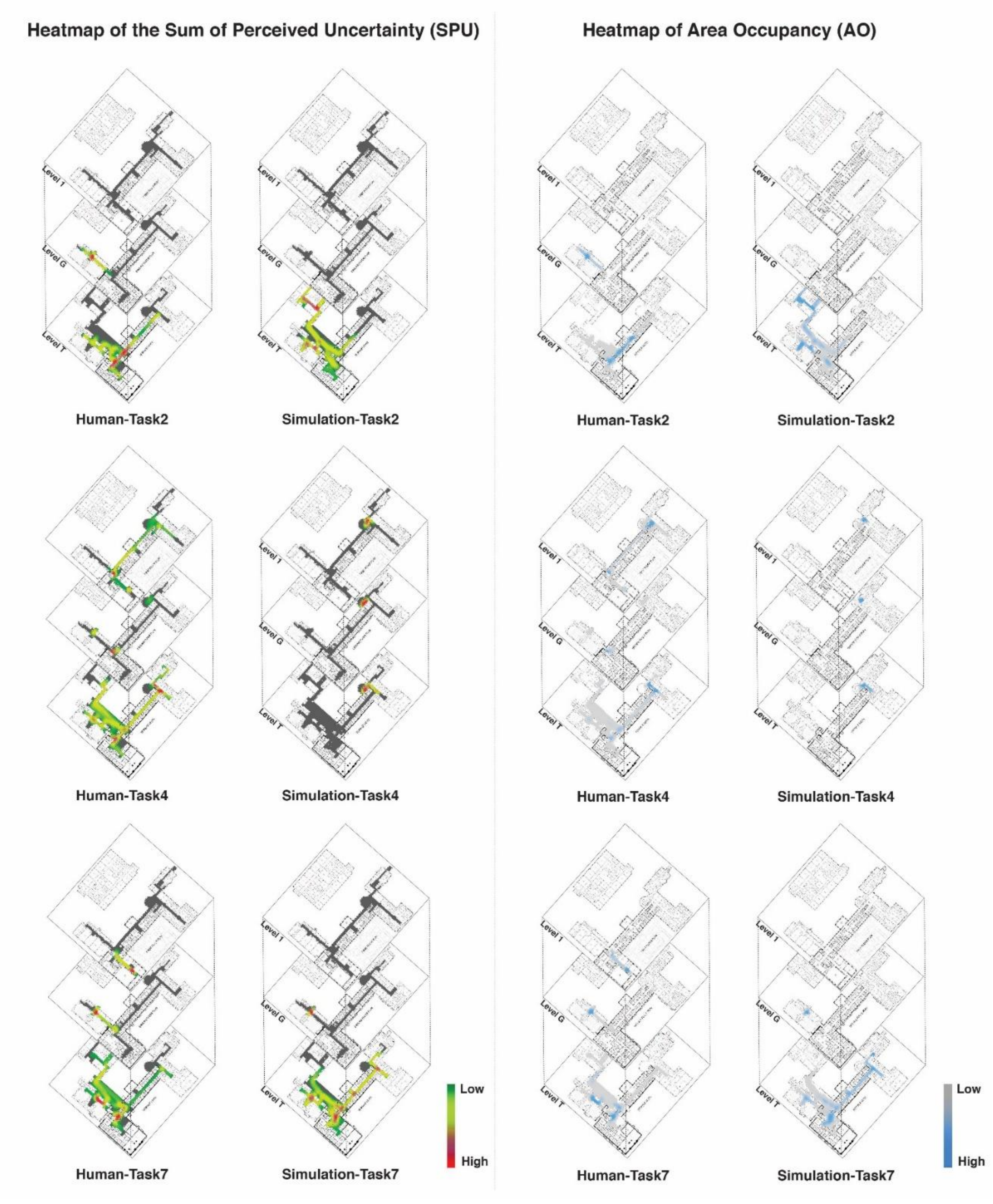
5.6.1 Insights from Simulation on Wayfinding Design

One important finding in our research is that ***Dimension Matters***. The time elapsed since the most recent encounter with a helpful sign was one of the strongest predictors of perceived path uncertainty. For designers, this means that even when alternative routes are not available it is important to add regular "confirmational" signs to help wayfinders affirm that they are on the right path [91]. When corridors extend for too long without such information it may lead to greater feelings of uncertainty and even fruitless backtracking. Wayfinding modelers also need to take this finding into account, especially since it is common for simulations to ignore the length of non-branching corridors. Traditional approaches that model the environment as a graph often overlook this dimension [90].

Second, our findings highlight the importance of ***Crucial Intersections.*** The wayfinding tasks that created the greatest problems for both humans and simulated agents were those that contained intersections where a wrong choice could divert the wayfinder into fruitless terrain where there was little indication of how to get back to the correct route. This was especially problematic for the simulated agents, which tended to become lost in the fruitless terrain for extended periods of time. However, such wrong turns were also a notable source of uncertainty and wasted time for the human participants. This is in contrast to most of the intersections in our wayfinding tasks, in which wrong turns led to areas with relevant sign coverage and alternative, albeit lengthier, routes to the destination. We suggest that designers should seek to identify any crucial intersections where there is a possibility of diversion into fruitless terrain, and take steps to mitigate that problem with heightened directional cues at the intersection and/or recovery signs that would make a wrong turn less destructive. Simulations such as PATH-U that provide high-resolution spatial-temporal metrics can be useful in identifying these crucial intersections across numerous wayfinding tasks.

Finally, designers should strive to ***Prevent Missed Routes***. High uncertainty and wasted time occurred in our study for some participants and agents that overlooked a correct route option. Once the route was overlooked, they tended to become stuck in a loop of backtracking and searching, unable to differentiate fruitless from promising terrain. In some cases, it was the final destination itself that was overlooked, as participants walked right past the destination several times while continuing to backtrack and search for directional signs. Design strategies to avoid missed routes should center around highlighting the salience of intersections and destinations to ensure that wayfinders do not walk past them unaware. Visual connections and a more open layout may be useful in helping wayfinders to recognize when there is an available route that they have overlooked [93].

Figure 29 Heatmap of the Sum of Perceived Path Uncertainty and Area Occupancy of Task 2, 4, 7



5.7 Limitations and Future Works

Although the current study was grounded on a respectable sample size and multiple wayfinding tasks, it could benefit from collecting data from more participants and in diverse buildings (e.g., hotels, transportation hubs, and healthcare facilities) to improve the generalizability of the model. The validation could also be strengthened by using a larger sample size and a different building, and by directly comparing PATH-U against output from other existing wayfinding models beyond A*. Some of this expanded work is planned for future studies.

Researchers have noted that perceived path uncertainty can arise from various sources [3,7]. Our model's predictions are based on uncertainty arising from the distribution of directional signs and available route choices in a specific building typology, along with the agent's spatial abilities. The model does not account for other sources of uncertainty, such as degraded or misplaced signs, crowded passageways, or dim lighting conditions. Moreover, the data used to develop the model was derived from a convenience sample of younger adults, which will limit its generalizability to other indoor environments. Additionally, our model did not incorporate participants' pre-existing emotional states, which can influence their perception and stress levels, potentially affecting the accuracy of our predictions regarding perceived uncertainty. Though our real-world experiment provides a realistic wayfinding context and experiences, it is affected by confounding factors such as events, crowds, and natural lighting. Designers who use the simulation should understand these limitations and recognize that many features of the environment are not considered in its output. As the building simulation field continues to advance, it is likely that we will discover many novel ways to expand the information that models can consider.

Future research in this area should also seek to improve the wayfinding heuristics that shape the agents' responses to environmental variables. While our simulation included a few basic heuristics, such as prioritizing searches for floor-level transition points, it does not fully reflect the complexity of human cognition during wayfinding. Creating simulated agents that are able to engage in more reasoning about the environment will strongly advance the realism and utility of our model. One important direction is to examine and simulate the feedback loop between experiences of uncertainty and subsequent wayfinding behaviors, specifically focusing on information-seeking and backtracking. Our analysis suggested that human participants did not consistently follow the "floor strategy" and "follow your nose" (continue straight ahead) heuristics, but instead engaged in much more complex behaviors. By carefully evaluating these strategic responses in conjunction with empirical research, wayfinding simulations can better model how environmental cues translate into diverse behaviors.

Finally, although our model includes two variables that can be adjusted to reflect individual differences (spatial abilities and prior knowledge of the building), wayfinding simulations can benefit from developing a much larger variety of agents with different abilities and proclivities. This approach can help designers to better consider the experiences of wayfinders from diverse backgrounds. In addition to incorporating behavioral parameters such as risk-taking proclivity, models could also be designed to simulate agents with perceptual differences (e.g., color-blindness), mobility limitations, language barriers, and other relevant variables.

5.8 Conclusion

In this paper, we present an integrated wayfinding model named PATH-U, which was designed to complete multi-level, semi-guided wayfinding tasks without prior knowledge of the environment and predict areas in the building where human wayfinders might feel uncertain. The model was enhanced by incorporating visual perception, natural movement, short-term memory, and wayfinding heuristics. The uncertainty prediction model was based on data from 39 real-world participants conducting seven wayfinding tasks, and PATH-U's performance was validated at both the task performance level and the fine-grained spatial-temporal level. Our findings support the conclusion that designers should focus on providing additional wayfinding guidance at critical intersections and long corridors, and ensuring the salience of intersections and destinations to avoid missed routes. Tools such as PATH-U can be helpful in identifying crucial and problematic intersections and checking for issues that a designer may have overlooked. To further enhance simulation realism, we recommend that future studies incorporate enhanced reasoning heuristics as well as more diverse agents grounded in continuing empirical study of human wayfinding behaviors.

Chapter 6. Rhythm of Guidance Affects Human Wayfinding Behaviors and Experiences

Feature importance analysis in Chapter 5 indicates that the elapsed time since receiving helpful guidance correlates with perceived uncertainty. Building on this finding, the present chapter reports a controlled study that examines the causal impact of guidance rhythm on perceived uncertainty, as well as on wayfinding performance and experiential measures such as anxiety and curiosity.

6.1 Background

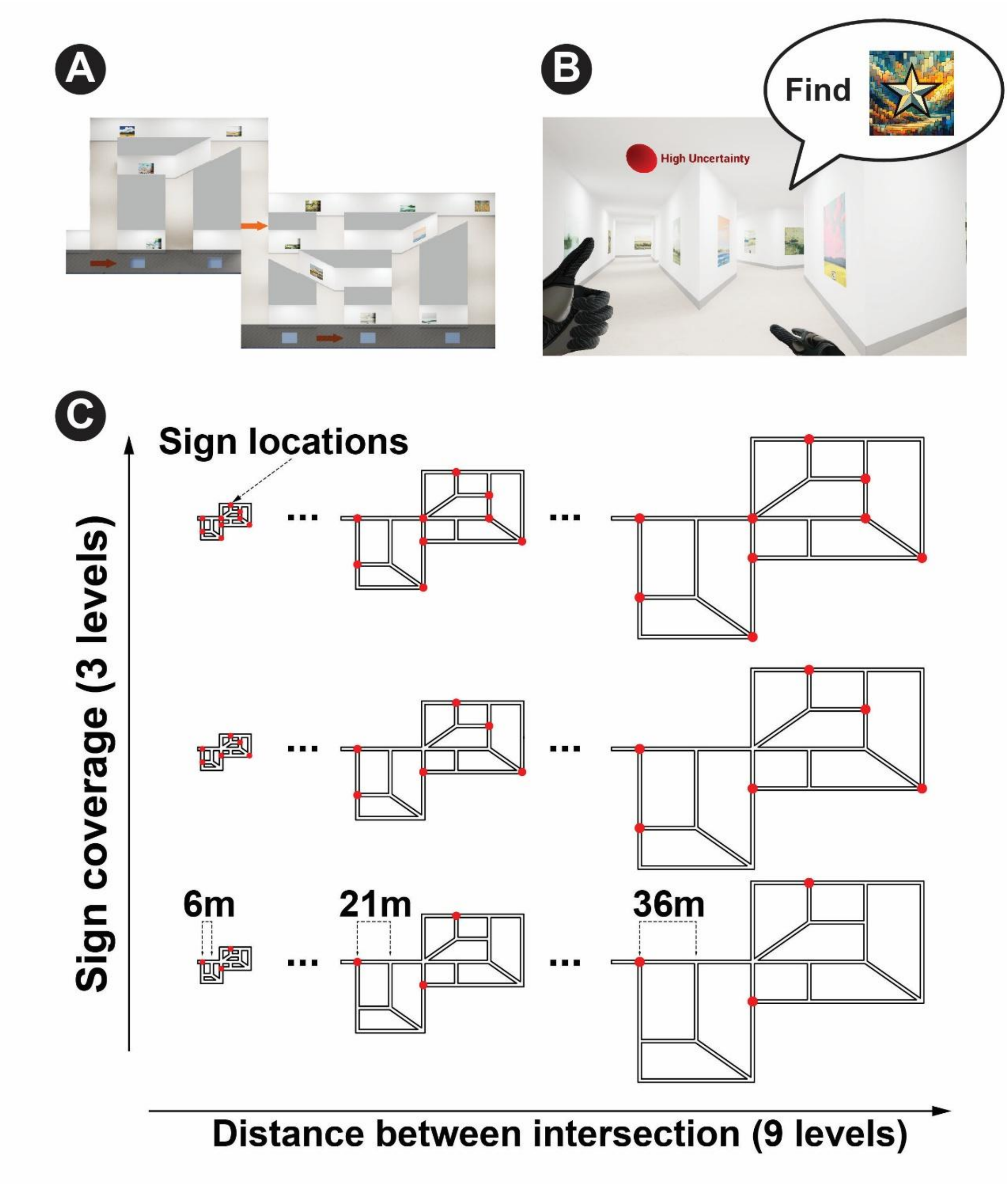
Wayfinding, the process of navigating through unfamiliar environments to reach a desired destination, is a fundamental human activity [1]. Ineffective wayfinding imposes significant societal costs, including wasted time, economic losses, psychological distress, and, in critical settings like hospitals or emergency exits, risks to life. As built environments grow increasingly intricate and global demographics shift toward older populations, understanding how environmental design shapes wayfinding performance and mental health has become urgent for creating inclusive, human-centered spaces.

Traditional empirical research has focused on static environmental variables such as signage, visibility, spatial layout, landmark, and their relationships with wayfinding performances [155,229,238,239]. While such studies provide foundational insights, they often neglect the dynamic interplay between humans and environments. Wayfinding is not just a sequence of isolated discrete decisions but a temporally evolving process where navigators accumulate spatial knowledge, experience fluctuating emotions (e.g., curiosity, anxiety), and adapt strategies in real time [65,78,240]. This dynamism is also central to architectural theories of "rhythm," which describe how spatial transitions and sensory cues create temporal patterns that shape user experience. Yet, despite its conceptual resonance, the rhythm of guidance—defined here as the temporal distribution and density of navigational cues—remains empirically underexplored in wayfinding research.

A critical gap lies in understanding how rhythmic variations in guidance influence both performance and experiential outcomes. Psychological frameworks [4,7], posit that perceived uncertainty—a hallmark of wayfinding in novel environments—elicits divergent affective responses: it can stimulate exploratory behavior and curiosity [18,24] or provoke anxiety and avoidance [3,22]. For instance, museums may intentionally leverage rhythmic uncertainty to foster engagement, whereas airports require consistent predictable guidance. However, existing studies operationalizing guidance fails to capture how temporal patterning modulates these effects [155,241]. Similarly, computational methods like space syntax sometimes reduce environments to topological graphs and isolated metrics, simplifying the continuous experience of moving through transitional spaces where guidance rhythms manifest [64,142,242].

This study bridges these gaps by investigating how the rhythm of guidance impacts wayfinding behaviors and experiences at a fine-grained, dynamic level. We hypothesize that rhythmic patterns of guidance exert non-linear effects on navigational performance and emotional states, mediated by the interplay of two novel variables: (1) distance between intersections (DBI), which determines the temporal spacing of decision points (9 levels), and (2) sign coverage (SC), which modulates the density of directional cues (3 levels) (Figure 30). By maintaining identical topological layouts in virtual reality (VR) experiments, we isolate rhythmic variables while controlling for confounding geometric factors. Using data from 239 participants in a 9×3 factorial design, we assess performance metrics (travelled distance, time, backtracking) and experiential states (continuous self-reported uncertainty, anxiety, curiosity).

Figure 30 (A) One Example of VR Environment (B) First Person View of the VR Environment and Wayfinding Task (C) 9x3 Experiment Design

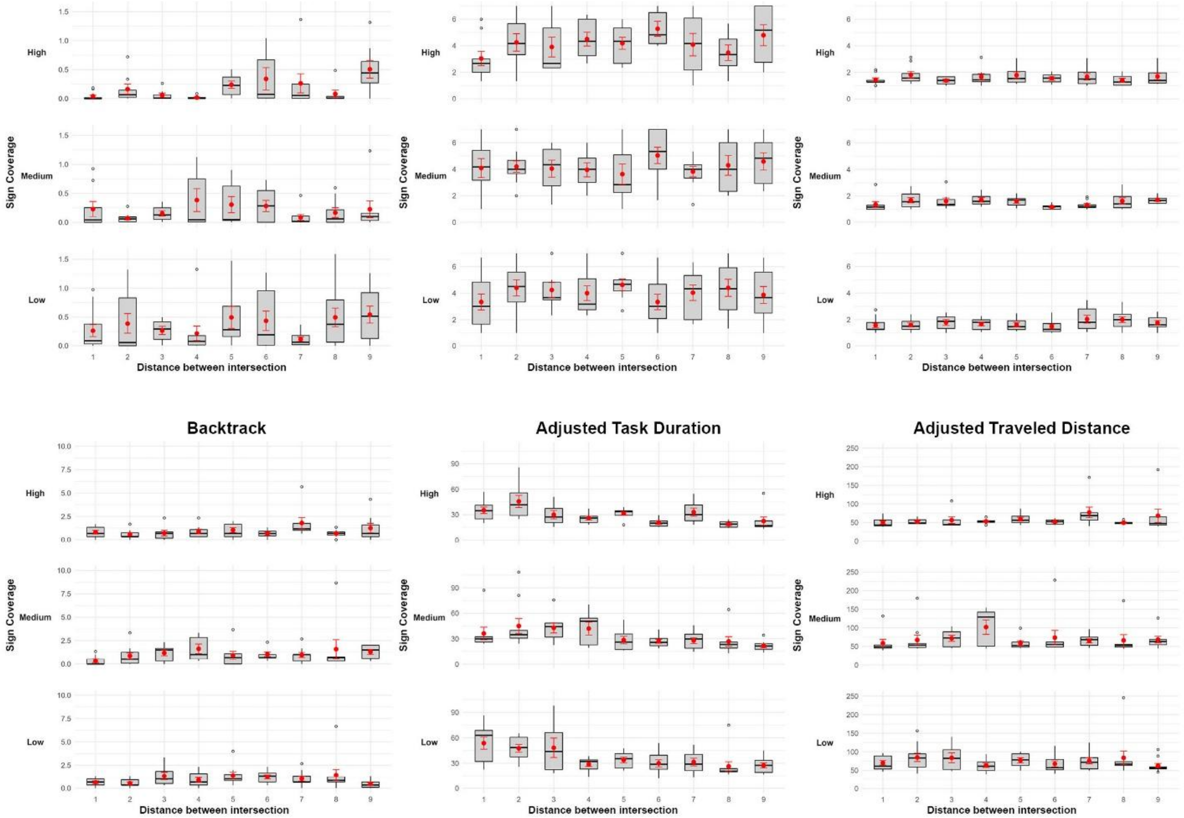


6.2 Results

6.2.1 Perceived Uncertainty

The model revealed a statistically significant effect of the combined linear terms of sign frequency and level on uncertainty, F(2, 224) = 7.40, p = 0.0008. Specifically, sign coverage had a significant negative linear effect on uncertainty (β = –0.084, p = 0.004), indicating that as signage increased, participants experienced lower uncertainty. Distance between intersection (DBI) also showed a significant positive linear effect (β = 0.089, p = 0.015), suggesting that uncertainty increased with greater environmental complexity (Figure 31). However, neither the interaction term (β = 0.029, p = 0.51) nor the quadratic terms were significant, and neither

Figure 31 Descriptive Statistics with Means and Confidence Intervals for Each Condition Across Six Outcome Measures

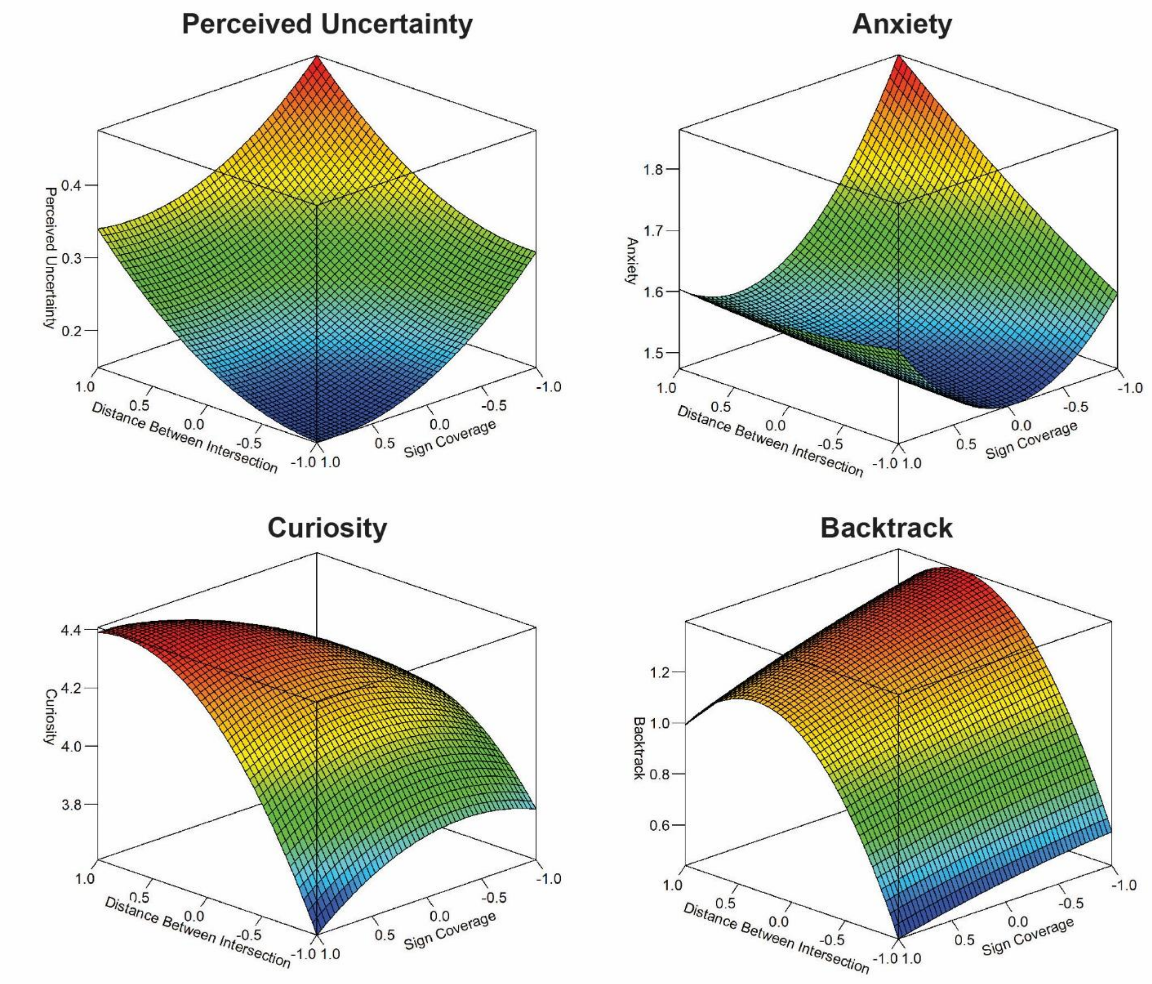


contributed significantly to the overall fit of the model ($p > 0.05$). The overall model was significant, $F(5, 224) = 3.46$, $p = 0.0049$, explaining approximately 7.2% of the variance in uncertainty (adjusted $R^2 = .051$). These findings suggest that participants' uncertainty was most strongly influenced by the additive linear contributions of distance between intersection and sign coverage, rather than their interaction or curvilinear effects.

6.2.2 Curiosity and Anxiety

Although the overall models for anxiety ($F(5, 224) = 1.42$, $p = 0.22$, adjusted $R^2 = 0.009$) and curiosity ($F(5, 224) = 0.65$, $p = 0.66$, adjusted $R^2 = –0.008$) were not statistically significant, the fitted surfaces revealed interpretable trends for future explorations. For anxiety, a marginal quadratic effect of sign frequency was observed ($\beta = 0.14$, $p = 0.089$), with lowest and highest sign coverage associated with slightly elevated anxiety, particularly under high distance between intersection. Similarly, the surface for curiosity suggested a subtle peak in environments with more guidance and high distance between intersection, though no model reached significance ($p > 0.05$). These surface plots (Figure 32) offer qualitative insights into how combinations of signage and spatial layout may shape participants' psychological responses.

Figure 32 Response Surfaces of Perceived Uncertainty, Anxiety, Curiosity, and Backtrack



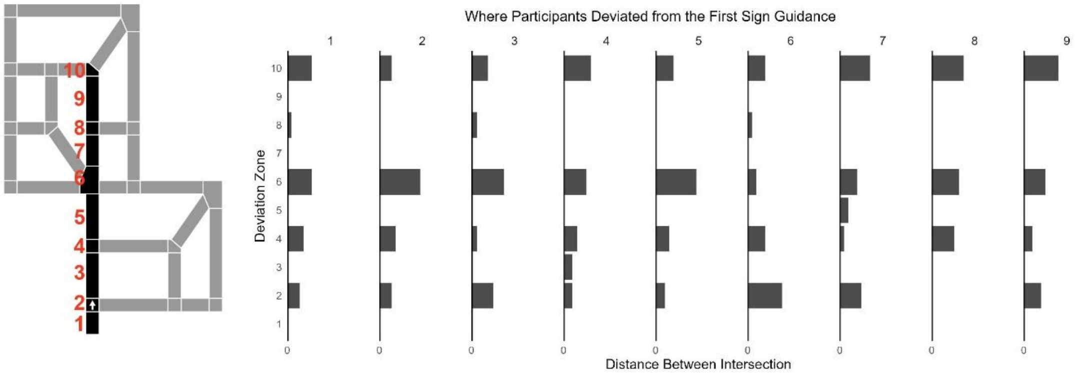
6.2.3 Wayfinding Performance

The model for travelled distance revealed a significant overall effect (F(5, 224) = 2.71, p = 0.021), with sign frequency showing a significant negative linear association (β = –8.13, p = 0.001), indicating that increased signage was associated with shorter distances traveled. Neither the quadratic nor interaction terms were significant ($p > 0.05$), and the model accounted for approximately 5.7% of the variance in travelled distance (adjusted $R^2 = 0.036$). The task duration model also yielded a significant fit (F(5, 224) = 12.02, $p < 0.001$, adjusted $R^2 = 0.194$). Both sign coverage (β = –3.37, p = 0.007) and distance between intersection (β = –10.76, p < 0.001) were associated with reduced task time, suggesting that higher sign coverage and longer distance between intersection facilitated faster completion. In contrast, though the backtrack model did not reach statistical significance (F(5, 225) = 1.59, p = 0.163), the linear effect of distance between intersection was significant (β = 0.31, p = 0.039), suggesting increased backtracking in environments with longer interval of guidance.

6.2.4 Sign Following Behaviors

We did not find significant evidence that the distance between intersections and the sign coverage affected the likelihood of participants following the sign-indicated route. To further examine participants' initial sign-following behavior, we isolated Task 1 and analyzed whether increasing the distance between intersections influenced the location at which participants began to deviate from the first sign's guidance. A linear regression model did not yield a significant effect (p = 0.30), suggesting no reliable linear trend in how early or late participants diverged. However, visual inspection of the distribution suggested that the deviation zone varied across levels. This was statistically confirmed by a Chi-square test of independence, which revealed a

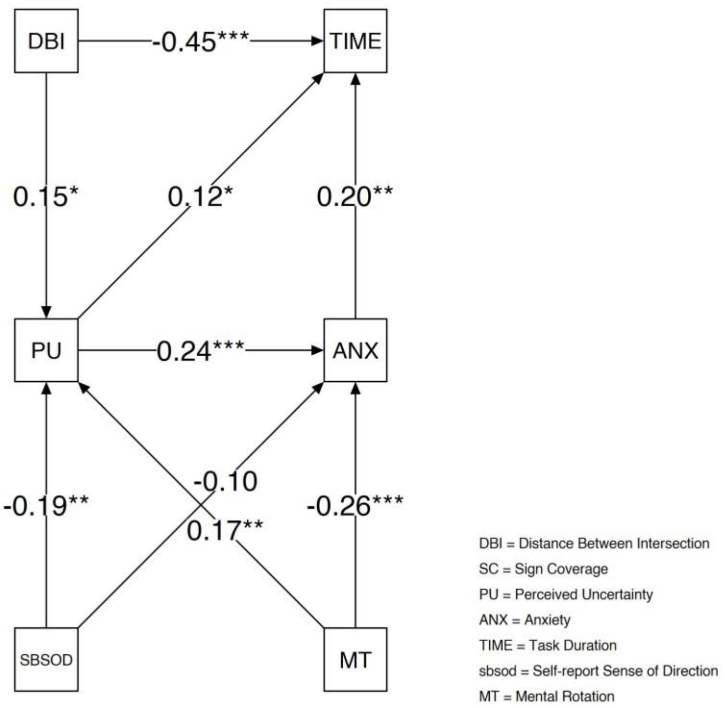
Figure 33 Distribution of the Zone Index Where Participants Deviated From the First Sign Guidance



significant association between spatial complexity level and the zone in which participants deviated from the first sign guidance, $\chi^2(48) = 67.20$, $p = 0.035$. The result suggests that the location of deviation is not independent of distance between intersection, even if the central tendency did not change significantly (Figure 33).

6.2.5 Path Analysis

Figure 34 Path Analysis of How Distance Between Intersection and Individual Traits Affect Wayfinding Performance and Experiences



The path analysis examined how spatial and cognitive factors influenced wayfinding experience and performance, with a focus on perceived uncertainty, anxiety, and task duration (Figure 34). The model revealed several significant direct effects. Higher distance between intersections (DBI) increased perceived uncertainty ($\beta = 0.15$, $p < .05$) but actually reduce task duration ($\beta = –0.45$, $p < .001$). Regarding the indirect effects, perceived uncertainty, significantly predicted anxiety (β = 0.24, p < .001), and increased task duration (β = 0.12, p < .001) supporting its role as a mediating psychological state in the wayfinding process. We observed a competitive mediation between DBI and task duration.

Cognitive abilities also played a role: better mental rotation performance was associated with lower anxiety (β = –0.26, p < .001), and self-reported sense of direction negatively predicted uncertainty (β = –0.19, p < .01). These results suggest that both environmental rhythm and individual differences shape wayfinding outcomes, with perceived uncertainty serving as a significant psychological mediator.

6.3 Discussion

This study provides empirical evidence that the rhythm of environmental guidance, which refers to the temporal spacing and density of navigational cues, plays a critical role in shaping both wayfinding behavior and subjective experiences such as uncertainty, anxiety, and curiosity. Response surface analysis revealed heightened curiosity in environments that were both extensive and well-guided. This outcome likely stems from consistent guidance within a complex spatial layout, which sustains uncertainty at a manageable level while maintaining a high rate of information gain [255].

Analysis of route choice deviations from the first sign revealed a roughly bell-shaped distribution of participants diverting from the initial guidance at zone 6 (Figure 33), suggesting a parabolic relationship in exploratory behavior. This finding supports theories positing that curiosity is most pronounced when uncertainty is neither too high nor too low, but rather balanced and accompanied by ongoing feedback. In contrast, environments characterized by low uncertainty, whether resulting from simplicity or excessive guidance, tended to suppress curiosity, aligning with prior work that links predictability with reduced engagement. These results support theoretical models of curiosity and uncertainty in the wayfinding context [255], and also resonate with Lawton’s environmental press theory [254], which posits that adaptive behaviors emerge from the interplay between environmental demands and individual competence. Notably, this study extends Lawton’s framework by viewing competence and environmental press as dynamic rather than static variables, suggesting that optimal adaptation may involve multiple trajectories rather than a single ideal zone.

The findings also challenge the dominant focus on decision points in wayfinding research. Participants often reported feelings of uncertainty while walking through seemingly simple corridors, suggesting that uncertainty experienced between landmarks or signs is a critical but frequently overlooked aspect of navigation.

A particularly counterintuitive finding was that participants in larger mazes, despite experiencing higher levels of uncertainty, were more likely to follow initial sign guidance rather than exploring alternative paths. This pattern suggests increased reliance on available cues in unfamiliar environments, potentially driven by risk aversion or diminished perceived competence. However, when comparing environments from the smallest to medium size, we observed a growing tendency toward exploration in response to uncertainty. This indicates that individuals employ different coping strategies depending on the level of uncertainty. Common heuristics, such as “following the nose” [235] or making random choices in the absence of guidance [253], capture only a subset of navigational behaviors under uncertainty. These findings underscore the dual effect of uncertainty and highlight the need to further investigate how perceived uncertainty interacts with dynamic coping mechanisms during wayfinding.

Methodologically, this study advances the field by integrating immersive virtual reality with realistic locomotion techniques. This approach allows for the recruitment of larger and more diverse participant samples than traditional laboratory or field studies. By systematically varying key spatial parameters, the study reveals the dynamic and nonlinear relationships between environmental features and navigational behavior.

6.4 Methods

6.4.1 Participants

An a priori power analysis was conducted using G*Power (ANOVA, effect size = 0.25, $\alpha = 0.05$, power = 0.80), indicating a required sample size of 324 participants (12 per each of 27 conditions). A total of 305 participants were recruited via two methods: in-person recruitment in public spaces and the university's SONA system. Sixty-six participants were excluded due to withdrawal, software errors, or experimenter mistakes, resulting in 239 valid datasets. Participants ranged in age from 17 to 67 years (M = 23.90, SD = 9.03), In terms of gender, 131 identified as female, 102 as male, 6 as non-binary.

All participants provided informed written consent. The study protocol was approved by the Institutional Review Board at Cornell University. Participants received either course credit or a $10 gift card as compensation.

6.4.2 Procedure

Each experimental session began with participants completing an online survey consisting of the informed consent form, a demographic questionnaire, the Santa Barbara Sense of Direction Scale, and the Intolerance of Uncertainty Scale. Following the survey, participants were fitted with a Quest 2 VR headset and trained to use the VR joystick.

Participants were then introduced to a training scene in the virtual environment, where they received instructions on the experiment context and wayfinding tasks via an on-screen widget displaying written prompts. During the training, participants practiced navigating and orienting themselves in VR, reporting their perceived uncertainty levels, and completing in-VR surveys after each task. The practice session continued until participants successfully demonstrated their understanding by accurately reporting perceived uncertainty levels and completing the virtual surveys as instructed.

After completing the practice, participants proceeded to the three experimental wayfinding tasks, completed sequentially. Upon finishing the tasks, the Mental Rotation Test was administered before concluding the session.

6.4.3 Wayfinding Task Design

In each task, participants were primed to be in a virtual hospital environment and instructed to find a friend's ward, marked by a star image. To minimize the influence of prior spatial knowledge or logical associations, the goal of the tasks was intentionally abstract and unfamiliar, avoiding real-world references such as room number reasoning or logical associations with semantic destinations (e.g. café).

The maze was designed using a grid layout to emulate common public building configurations, including loops and star-shaped pathways [243,244]. To diversify intersection complexity and task difficulty, diagonal routes were introduced after feedbacks from pilot testing. The mazes varied in size, ranging from 6 m to 36 m, with intermediate dimensions evenly distributed. The environment was intentionally minimalistic, containing only essential surface materials, lighting, and wall paintings, while excluding furniture and functional fixtures (e.g., fire alarms) to eliminate extraneous navigational cues.

Navigational information was provided through two primary sources. The first source was directional guidance, presented as arrows on the floor pointing toward the shortest path when participants approached intersections with signage. The arrows were visible only upon entering an intersection, simulating real-world sign-reading behavior in which wayfinders know whether a sign at an intersection contains useful information only after approaching it. Three levels of signage coverage were implemented by placing 3, 6, or 9 signs at different intersections. The second source of information was a set of 50 wall paintings marked with random numbers at regular intervals. These paintings served to obscure the goal image and functioned as landmarks to adjust task complexity.

Participants navigated the virtual environment using a discrete locomotion technique, which allowed them to teleport maximum of 1 m at a time. They rotate in place physically to orient in the virtual environment. This method preserved the cost of travel and provided a continuous visual flow similar to physical wayfinding. It was chosen over other navigation methods, such as continuous locomotion or unrestricted teleportation, to minimize motion sickness while maintaining ecological validity in wayfinding [245,246].

6.4.4 Measures

To assess participants' wayfinding experiences, we measured self-reported curiosity, state anxiety, and continuous perceived uncertainty.

Curiosity in existing studies commonly employ a single-item measure such as "How curious are you about something?", especially in paradigms involving trivia questions [21,24] or other curiosity-related contexts requiring repeated measurements [247]. which helps reducing the variance in single-item questions from individual. This approach helps mitigate variance typically introduced by individual differences in single-item responses. While some research has introduced multi-item scales—for instance, a 7-item Likert scale developed in the study [248]—such items were designed for different contexts and are not well suited for environmental exploration. Therefore, in our study, state curiosity was measured using a modified single-item question: "How curious do you feel about the environment?".

State anxiety was assessed using the five-item form from the Spielberger State-Trait Anxiety Inventory (STAI-S), a validated and reliable scale for measuring state anxiety [215].

Continuous perceived uncertainty was measured using an adapted version of a joystick-based interface from our prior study [216]. In this system, participants continuously reported their moment-to-moment uncertainty by engaging with a handheld VR controller. The design allowed for three levels of perceived uncertainty based on participants' natural hand gestures: (1) low uncertainty when no buttons or triggers were pressed ("letting loose"), (2) medium uncertainty when either a button or a trigger was pressed, and (3) high uncertainty when both were pressed simultaneously ("forming a fist"). This interaction metaphor closely mimics embodied expressions of hesitation and confidence, facilitating intuitive and continuous reporting of uncertainty.

To evaluate wayfinding ability, we included both subjective and objective measures. Subjective wayfinding ability was assessed using the Santa Barbara Sense of Direction Scale (SBSOD), a widely used self-report measure of an individual's perceived navigational skills [142,180]. Objective wayfinding ability was measured using a mental rotation task, which assesses spatial cognitive ability linked to successful navigation [181]. We did not include additional subjective spatial measures such as the Spatial Anxiety Scale or the Spatial Perspective-Taking Scale, as our prior research revealed high intercorrelations among these instruments [216]. In this study, SBSOD emerged as the strongest predictor of perceived uncertainty and wayfinding performance, justifying its exclusive use here.

Finally, we measured intolerance of uncertainty using a validated trait-scale, given prior findings suggesting that individuals with higher intolerance of uncertainty are more likely to exhibit uncertainty-related behaviors during navigation [249].

6.4.5 Analysis

To examine the individual and interactive effects of our two key independent variables—distance between intersection and sign and sign coverage—on participants' wayfinding outcomes, we employed the Response Surface Methodology (RSM). It is particularly useful for exploring the optimal conditions of experimental factors and for understanding both main effects and interactions through second-order (quadratic) models. Prior to analysis, outcome measures from the three wayfinding tasks were averaged to generate a composite score for each participant.

To compute backtracking counts for each participant's trajectory, we first transformed raw location data into zone codes, representing discrete spatial areas. A backtracking event was defined as a return to a previously visited zone (e.g., an A–B–A pattern in the zone sequence was counted as one backtrack). To reduce false positives—particularly those caused by lingering near zone boundaries—any return to a previous zone was only counted as a backtrack if the interval between visits exceeded 5 seconds. This threshold ensured more accurate identification of intentional navigation errors or uncertainty-driven reversals.

We also quantified sign-following behavior, defined as a movement sequence in which a participant, after encountering a sign in a zone, proceeds to the adjacent zone in the direction indicated by the sign. Each such instance was counted as one sign-following event.

To analyze initial sign-following behavior, we focused on data from Task 1 under Sign Conditions 1 and 2, where participants had no prior exposure to the environment. This constraint ensured that observed behaviors reflected initial navigational responses uninfluenced by prior learning. We excluded data from Sign Condition 3, as its high sign coverage placed another sign in the middle of the central path (zone 1 to zone 10), biasing the effect of the first sign. For each level of the distance variable, we identified the zone index at which participants first deviated from the direction indicated by the first sign, and calculate the occurrences of each zone index.

Chapter 7. A Cognitive Wayfinding Model PATH U.2 Replicates Human Route Diversity and Perceived Uncertainty in Unfamiliar Indoor Environments

In the previous chapter, I presented the modeling and validation of the PATH-U agent. This model integrates a symbolic representation of human route choice in unfamiliar environments with a data-driven prediction of perceived uncertainty, demonstrating comparable patterns to human performance and uncertainty in certain tasks. However, several limitations remain.

Theoretically, the PATH-U agent operates on a graph-based representation that assumes decision-making occurs only at intersections, overlooking cognitive processes during corridor traversal. Its short-term memory model assumes perfect recall after each route is traversed, and its intersection-level decision-making relies on rule-based heuristics, resulting in deterministic behavior that fails to capture individual differences in route choices. While the data-driven uncertainty prediction offers useful insights, it lacks generalizability and interpretability, and is constrained by the unavailability of high-quality spatiotemporal datasets in indoor environments.

Practically, similar to other models for unfamiliar environments, the PATH-U agent requires substantial manual setup of decision nodes and zones. This subjectivity introduces variability, as different prescriptive configurations can significantly affect simulation outcomes.

Building on these insights, the next chapter introduces the PATH-U.2 agent, designed to address these theoretical and practical limitations.

7.1 Background

As urban environments grow more complex and populations age, declining navigational abilities pose increasing challenges, especially in unfamiliar environments such as healthcare facilities and transportation hubs [64,187,250–252]. Poor wayfinding design can lead to wasted time, financial costs, and even loss of life. Thus, creating clear and inclusive wayfinding systems is crucial for enhancing accessibility, improving user experience, and ensuring safety in complex environments such as hospitals, airports, and urban spaces.

Designing effective wayfinding systems is challenging due to the complexity of human behavior and the multitude of variables involved in the design process. In unfamiliar environments, wayfinders perceive, reason, and act within their surroundings [65], engaging in continuous learning through dynamic interactions that are difficult to intuitively grasp. Designers must coordinate multiple variables, integrating signage systems with building layouts and architectural features—a practice known as "integrated wayfinding" in the industry. Implementing these strategies relies heavily on experience and intuition, and obtaining human feedback early in the design process is costly, introducing uncertainty to both the process and its outcomes.

To address these challenges, computational models of human behavior and simulations provide performance metrics and allow designers to explore bold strategies and identify potential failure modes [28]. However, most existing wayfinding models focus on traffic flow or evacuation scenarios, with few addressing first-time wayfinding in unfamiliar indoor environments [33,75–77]. These models often rely on task-level performance metrics, such as total distance traveled and time taken to reach a destination, which fail to capture the nuances of wayfinding experiences or to pinpoint specific problem areas [80,109,193]. Few models offer high-resolution spatial-temporal metrics like perceived path uncertainty, which can identify when and where individuals feel uncertain. One prior study incorporated perceived path uncertainty but did not account for dynamic cognitive state shifts and uncertainty-driven behaviors such as curious exploration or backtracking [253].

Our project addresses these gaps, grounded in the belief that high-resolution spatial-temporal metrics—such as moment-to-moment perceived path uncertainty—and dynamic uncertainty-driven behaviors, like exploration and backtracking, will provide more precise feedback and insights for designers. We developed a new model framework, “PATH-U.2” (Predictive Agent for Testing Human Uncertainty during navigation), which simulates partially guided indoor wayfinding without prior knowledge of the environment, offering spatial-temporal metrics for wayfinding experiences and performance. This model framework is scalable, based on a Cellular Automata framework that integrates diverse information sources, including spatial curiosity, sign guidance, and room number reasoning, while allowing for easy expansion, adaptation, and parameter tuning using empirical data. We also tested the symbolic model for perceived path uncertainty, grounded in psychological entropy and information theories, distinguishing it from purely data-driven approaches [253]. Moreover, we conducted comprehensive validation of our agent simulation against empirical human wayfinding trajectories and experiences, using physical-world datasets from healthcare and educational buildings.

7.2 Method

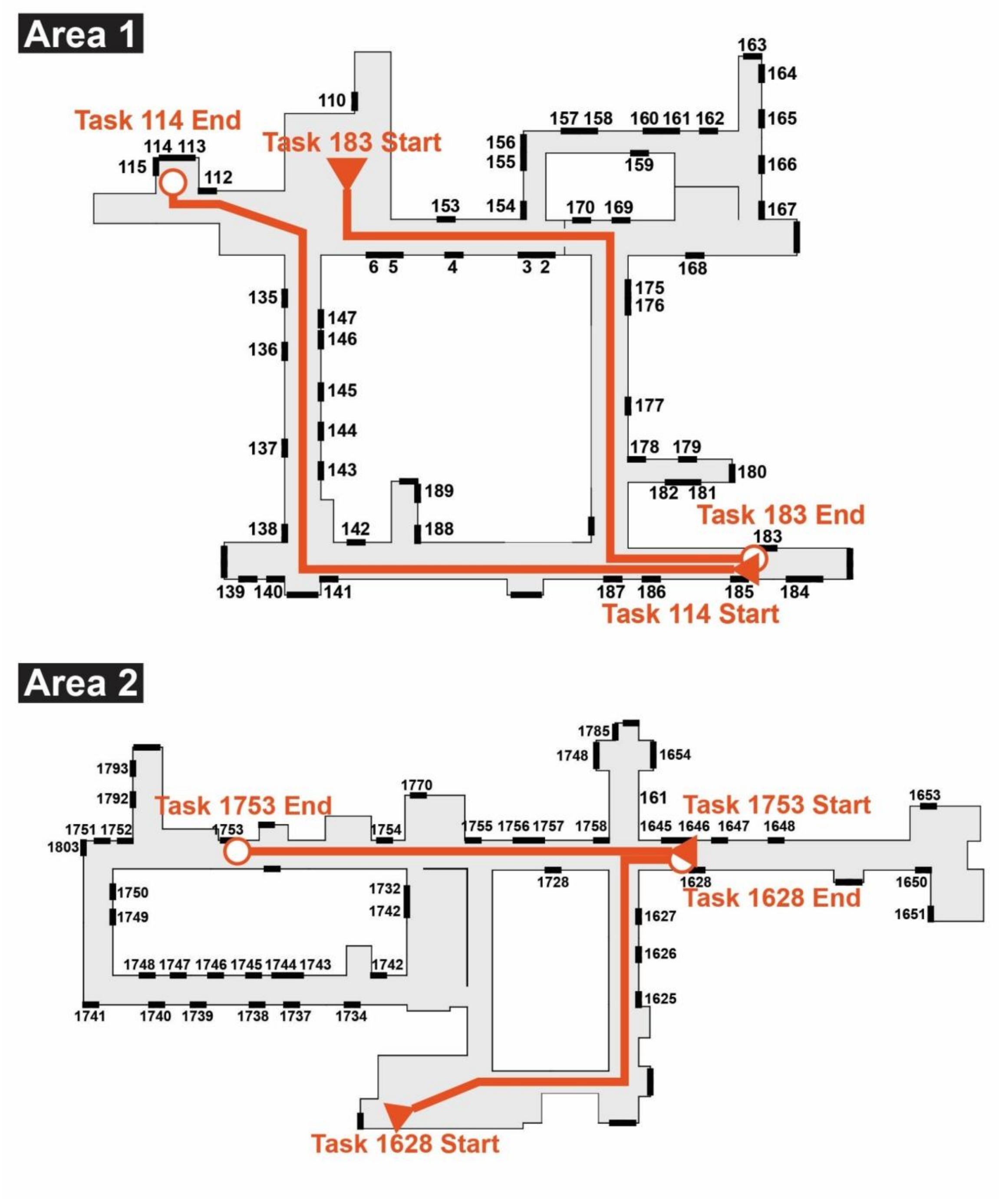
Our study aims to develop a surrogate model for a real-world system. This process primarily involves three steps. The first step is to collect evidence from empirical observation and literature. The second step translates that evidence into computational models. The third step verifies, validates the computational models, and evaluates their successes. This process, as suggested by one recent study [68], adheres to the Design Science Research (DSR) method [221]. This method emphasizes producing innovative and practical artifacts for real-world problems and includes three main components: problem identification, artifact development, and evaluation.

Our study follows a similar three-stage structure. In stage one, we reviewed the literature and conducted empirical studies to identify research gaps and behaviors of interest in unfamiliar indoor environments. In stage two, we proposed a CA-based model framework and computational methods for modeling exploration, sign reasoning, perceived path uncertainty, and uncertainty-seeking/aversive behaviors. Finally, we conducted a sensitivity analysis to evaluate the model behavior and performance. We also validate the model by comparing its prediction with human wayfinding data in a physical building.

7.2.1 Validation

We evaluate the model using three approaches. First, we conduct a sensitivity analysis to examine how variations in model parameters influence outcome measures across four distinct tasks. Second, we assess the model's ability to generate believable human route choices and replicate individual differences in human wayfinding trajectories, thereby evaluating our model's capacity and limitations. Third, we compare the model's performance metrics with empirical human wayfinding data to assess its predictive validity.

Figure 35 Four Wayfinding Tasks in Two Areas with the Shortest Paths



7.2.1.1 Validation Human Dataset

The validation dataset consists of trajectories from 69 human participants completing four wayfinding tasks in a newly constructed healthcare facility. As the building was undergoing pre-operational staff training, participants navigated the space with minimal crowd interference.

None of the participants had prior experience with the building. To reduce learning effects, they completed two wayfinding tasks in one area and the other two in a different area. Each task required participants to locate a room based on its number (183, 114, 1628, or 1753). These destinations were intentionally selected because no directional signage was available, requiring participants to rely solely on numerical reasoning to reach the target (Figure 35).

During data collection, a researcher shadowed each participant and used a tablet-based tool, WayFind, to log their location and timestamps on the floor plan. Simultaneously, participants used a joystick device to report their moment-to-moment perceived uncertainty, a method validated in my prior research.

7.2.1.2 Sensitivity Analysis Procedure

The sensitivity analysis involves varying heterogeneous parameters while maintaining specific constraints. The combined weight of spatial configuration and room number reasoning is fixed at 0.5, as the weight of directional guidance is always set to 0.5 to maintain dominance from the explicit information. Similarly, the weights assigned to sequence reasoning and difference reasoning sum to 1. Given these relationships, we varied four key parameters: the weight of spatial configuration, the weight of sequence reasoning, visual range, and visual distance (Table 11). Three outcome measures are chosen: trivial loops, travelled distance, and average perceived uncertainty.

To explore the parameter comprehensively, we employed Sobol sampling with N = 512, D=4, and enabled second-order analysis. However, due to computational constraints in the simulation setup, we discretized the visual range in 5-degree increments and the visual distance in 0.5-meter increments. This rounding operation resulted in fewer samples at the extreme values of visual distance and visual range, thereby violating the uniform distribution assumption required for Sobol's method. To address this issue, we used the Morris method to compute sensitivity indices, as it can accommodate non-uniform distributions. Ultimately, we generated 4,842 samples and verified the convergence of the Morris sensitivity indices by incrementally increasing the sample size and assessing the stability of the indices.

Table 11 Four Variables and Their Ranges for the Sensitivity Analysis

Variable	**Abbreviation**	**Range**
Visual Distance	Iso_{dist}	5-10m
Visual Range	Iso_{range}	90-120 degrees
Weight of Spatial Configuration	W_c	0-0.5
Weight of Room Number Difference	W_{diff}	0-1

7.2.1.3 Route Choice Validation

To assess the believability of agent route choice behaviors, we first establish an acceptability criterion to exclude clearly abnormal behaviors. This criterion is based on the number of trivial loops, defined as the proportion of repeated visits to any cell with a length of two or fewer. An agent is considered acceptable if it exhibits fewer than 10 trivial loops. This threshold, determined through observation, aims to exclude agents that exhibit excessive oscillation between two cells under specific parameter combinations while still allowing for normal backtracking behaviors.

To further analyze route choice, we divide the building layout into decision-making zones (Figure 46A). A decision zone is a location where a wayfinder must decide whether to continue along the current route or change direction. We translate human trajectories into sequences of zones and classify them into different types. Since some participants get lost, resulting in complex sequences, and to manage the complexity of route types, we group those that appear only once into the 'Others' category. In Task 3 (goal: 1628) and Task 4 (goal: 1753), we aggregate route types that exhibit slight variations but share a similar overall rationale, preventing each from being categorized individually under 'Others'.

We categorize agent trajectories into route choice types as human and visualize their distribution across the parameter space (Figure 40 - Figure 43). We then compare these distributions with human route choice sequences to assess whether our model effectively replicates key human route choice behaviors. We also examine the range of route choice diversity and how the diversity is distributed within the parameter space.

7.2.1.4 Performance Validation

To assess the validity of the agent's performance, we evaluate whether the simulation can accurately predict human wayfinding behavior in terms of both traveled distance and perceived uncertainty experience.

First, to analyze traveled distance, we ensure comparability between human and agent-generated routes by sampling the same number of route types as those observed in humans. If a specific human route type is not replicated by the agent, an equivalent number of eccentric trajectories is sampled from the "Others" category in the agent simulations. We then compare the mean traveled distance between acceptable agents and human participants. Additionally, we benchmark the agent's performance against a shortest-path algorithm to assess the extent to which the simulated trajectories align with human-like wayfinding patterns.

Second, to evaluate the agent's ability to capture perceived uncertainty experience, we compare the spatial distribution of perceived uncertainty across different tasks, examining whether similar patterns emerge in both human and agent wayfinding behaviors. We visually inspect whether the simulation identifies uncertain spots consistent with those observed in the empirical dataset. To further quantify these differences, we compute the average perceived uncertainty within each decision-making zone and rank the zones accordingly. Using the human-derived ranking as a baseline, we apply Earth Mover's Distance (EMD) [2] to measure the similarity between the human ranking and those generated by PATH-U.2, heuristic-based ranking (determined by the number of route choices), and random ranking. By accounting for the spatial proximity of zones, EMD provides a robust measure of similarity between the uncertainty distribution maps, capturing the minimal cost required to transform one ranking into another.

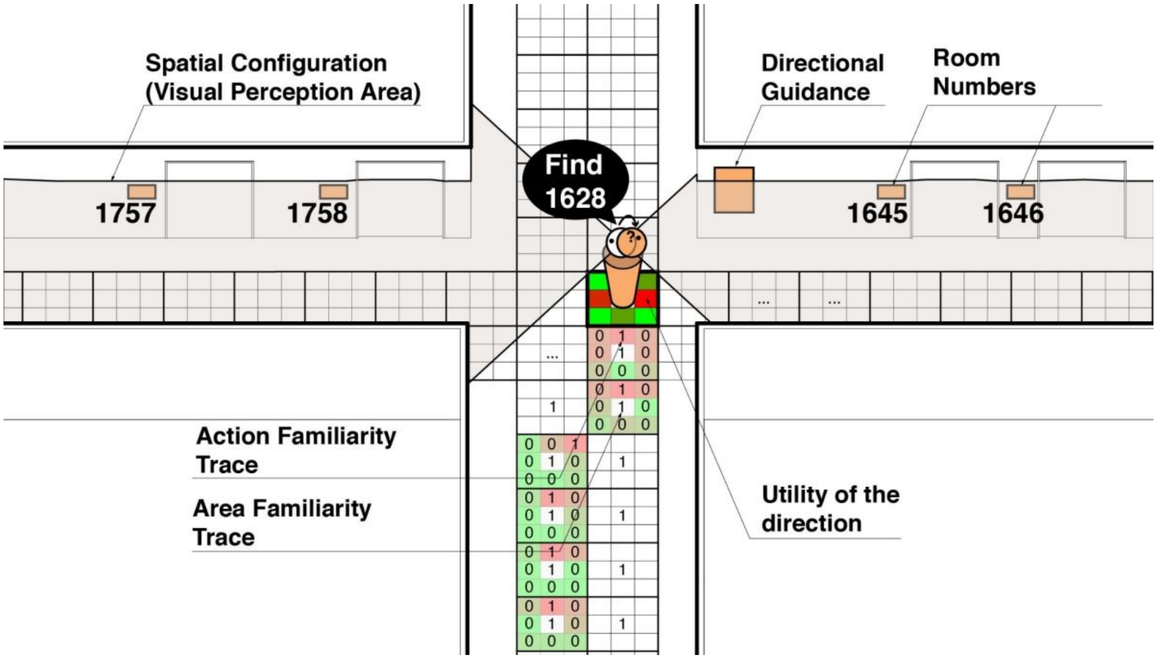
7.3 PATH-U.2 Agent Development

This section introduces the PATH-U.2 agent framework, detailing the rationale and methods behind modeling the environment, natural visual perception, memory, perceived path uncertainty, uncertainty-seeking and aversive behaviors, and information gain from various wayfinding sources. The framework is grounded on cognitive theories and designed to be scalable and adaptable, allowing the integration of additional information sources and wayfinding behaviors, such as memory decay, landmark usage, and cognitive maps, through minor refinements to model parameters and computations. It also accounts for individual differences and supports parameter optimization based on empirical datasets, ensuring flexibility and applicability in diverse scenarios.

7.3.1 Modeling the Environment

The navigable area is modeled using a grid of 1m x 1m square cells, commonly used in the Cellular Automaton (CA) model [119]. Compared to other environment modeling approaches, such as graphs, which require manual abstraction and omit travel between nodes, or continuous planes, which demand fine-grained definitions of agent position, velocity, and orientation, the cell-based method provides a balanced representation of spatial dimensions, choice set, natural movement, and computational efficiency in our case.

Figure 36 PATH-U.2 Agent Based on Grid World, Familiarity, and Information from Spatial Configuration, Directional Guidance, and Room Numbers



Each cell in a square grid has up to 8 adjacent cells, except where obstructions like walls or columns exist. At each time step, the agent selects one of these adjacent cells based on its expectation of which direction offers the greatest utility. A larger cell size (1m x 1m) is chosen compared to the commonly used 0.5m x 0.5m in evacuation simulations, which approximate the space occupied by a person and are suitable for multi-agent contexts. Since this study focuses on single-agent simulations, and most public corridors are approximately 1.5m wide, the chosen cell size avoids dividing such corridors into multiple horizontal cells, where information gain is assumed to be equivalent. This choice also improves computational efficiency while maintaining spatial fidelity.

7.3.2 Modeling the Visual Perception

We model natural visual perception using Unity's ray-casting function, which projects rays within a specified angle and distance, a method commonly used in the literature for modeling human-like visual perception [30]. The resulting hit points, combined with the agent's position, form a field-of-view mesh. Any objects, such as signs or rooms, intersecting this mesh are considered visible. The model assumes the entire interior height, from floor to ceiling, is within the field of view. To simulate typical human neck rotation when searching for environmental cues, the agent’s horizontal field of view span is set to 90-120 degrees, and the reading distance for signs is set to 5-10 meters [66]. The range represents imperfect perception across a 120-degree field and 10-meter radius. This study provides a flexible framework with parameters that users can easily adjust and expand.

7.3.3 Modeling the Utility of Information Sources

We model the utility from three information sources, spatial configuration $U_{configuration}$, sign guidance U_{sign}, and room number reasoning U_{room}. Utility gained from each information source is aggregated with individual weight. Since utility from each information source may have different ranges, we normalize them using the min-max normalization before aggregation where *i* represents different information sources and *t* represents the time step.

$$U^t_{normalized,i} = \frac{U^t_i - U^t_{min}}{U^t_{max} - U^t_{min}}$$

Spatial Configuration refers to the influence of geometric properties of space on people's route choices before encountering any wayfinding aids [101]. This intrinsic attraction, embedded in spatial experiences can be quantified using isovist metrics. A prior study showed isovist area could be a simple yet effective representation of utility from spatial configuration and led to believable navigation behaviors because bigger visual perception area implies more information [253]. In our model, it's calculated as the area of the isovist geometry, represented by $IsovistArea^t_i$.

$$U^t_{configuration,i} = IsovistArea^t_i$$

Directional Sign influences people's route choices by indicating the direction of the destination. The utility derived from a directional sign for direction *i* at time *t* can be modeled as the product of a fixed utility value α_{sign}, and an indicator variable, $DirectionPresence^t_i$. The indicator variable $DirectionPresence^t_i = 1$ if the sign indicates that the goal is in direction i, and 0 otherwise. The calculation is provided in the equation below.

$$U_{sign,i}^{t} = DirectionPresence_{i}^{t} \cdot \alpha_{sign}$$

Room Number Reasoning refers to the process by which people infer which route to take based on the sequence of room numbers, a common strategy in wayfinding scenarios where signs are absent and the goal is a specific room number. For example, if the goal is 1628, and one route begins with room 1635 while another starts with room 1700, people naturally tend to choose the route with the smaller numerical difference from the goal. We termed this decision-making strategy difference heuristics, represented by utility U_{diff}, which is also modeled in a previous study [253].

Additionally, people reason using numerical sequences. For instance, if the goal remains 1628, and one route displays room numbers increasing as "1635, 1636, 1637...", while another shows decreasing numbers like "1660, 1659, 1658...", individuals logically infer that the destination lies along the second route, where the sequence trends toward the goal. We termed this strategy sequence heuristics, represented by U_{seq}.

At times, difference and sequence heuristics may contradict one another, and individual differences influence the weighting of these strategies. To account for this, we model the utility of room number reasoning as the weighted sum of both heuristics, as described in Equation X, where $RoomPresence_{i}^{t} = 1$ if room numbers are visually perceived in direction *i*, and 0 otherwise.

$$U_{room,i}^{t} = RoomPresence_{i}^{t} \cdot (W_{diff} \cdot U_{diff,i}^{t} + W_{seq} \cdot U_{seq,i}^{t})$$

The $U_{diff,i}^{t}$ is calculated as the product of utility translation parameter α_{diff} and the smallest absolute difference between the *goal* and any room number *r* in the set $Rooms_{i}^{t}$, as shown in the following equation.

$$U_{diff,i}^{t} = \frac{\alpha_{diff}}{\min_{r \in Rooms_{i}^{t}} |goal - r|}$$

To calculate $U_{seq,i}^{t}$ from sequence heuristics, we define an indicator function f_{seq} to determine whether the perceived room sequence aligns with expectations based on the heuristic. If the agent perceives more than 2 rooms. The function considers the closest room r_{i1}^{t}, the second closest room r_{i2}^{t}, and the *goal*. The utility is calculated using the following equation. α_{seq} is another utility translation parameter.

$$U_{seq,i}^{t} = \alpha_{seq} \cdot f_{seq}(r_{i1}^{t}, r_{i2}^{t}, goal)$$

The indicator function $f_{seq}(r_{i1}^{t}, r_{i2}^{t}, goal)$ is defined as

$$f_{seq}(r_{i1}^{t}, r_{i2}^{t}, goal) = \begin{cases} 1 & (if\ (r_{i1}^{t} - r_{i2}^{t}) \cdot (r_{i2}^{t} - goal) < 0) \\ -1 & (\ otherwise) \end{cases}$$

7.3.4 Modeling the Decision-making

To decide the best movement direction for the agent, we combine them using a weighted sum. The agent deterministically chooses the cell with the maximum utility. The variation of weights accounts for individual differences, and can potentially lead to different route choice behaviors. For example, an agent might encounter a large open area on one side while receiving promising feedback from room numbers on the other. In such cases, variations in weighting can lead agents to make different directional choices. λ_i^t is the dynamic adjustment parameter determined by memory, which will be introduced in the section 7.2.6.

$$U_i^t = (W_c \cdot U_{configuration,i}^t + W_r \cdot U_{room,i}^t) \cdot \lambda_i^t + W_s \cdot U_{sign,i}^t$$

7.3.5 Modeling Memory

We use a dynamic familiarity trace method to model short-term memory during wayfinding in unfamiliar environments. Often, wayfinders experience the feeling of "I have been here before," which helps prevent repeated exploration of the same areas. Similarly, previous studies based on graph environments assign familiarity scores to edges, guiding agents to prefer edges with lower or higher familiarity scores. Although cognitive maps play a crucial role in wayfinding performance, empirical studies on unfamiliar environments suggest that cognitive map formation is limited during first-time wayfinding. Therefore, we did not incorporate cognitive map modeling into the memory module.

In the PATH-U.2 agent model, the agent leaves a familiarity trace on its current cell and surrounding cells at each time step. These traces adjust the information value derived from that direction. Before each step, the agent calculates the average familiarity trace from the perceived cells in direction i, denoted as $AreaTrace_i^t$. In addition, the agent leaves trace after taking an action at any cell, denoted as $ActionTrace_i^t$. In our simulation, the familiarity traces c_1, c_2 at each time step is set to 1. To mitigate the influence of extreme values, we apply a logarithmic transformation to both trace measures. The adjustment parameter λ_i^t is calculated as the following equation and the parameter γ_1, γ_2 is set to e in the simulation.

$$\lambda_i^t = {\gamma_1}^{-\log(AreaTrace_i^t)}{\gamma_2}^{-\log(ActionTrace_i^t)}$$

7.3.6 Modeling the Perceived Path Uncertainty

The information gain of each action U_i^t at the current agent's cell is translated to probability P_i via the normalization function in Equation X. A simple normalization method is chosen instead of other methods, such as a Softmax function, to avoid distorting the differences between the information values of each action. The perceived path uncertainty PU_i is calculated via Shannon's entropy in the equation X.

$$P_i^t = \frac{U_i^t}{\sum_{i=1}^{8} U_i^t}$$

$$PU_i = -\sum_{i=1}^{8} P_i^t \cdot \log_2 P_i^t$$

7.3.7 Model Assumptions

The PATH U.2 model is based on several assumptions. It assumes that the utility gained from each information source is independent, allowing the model to evaluate each source separately during decision-making. The environment is discretized into uniform cells, with the assumption that information gain is constant within each cell and that cell resolution remains consistent across all floor plans. The model also assumes perfect visual perception within the agent’s visual catchment area, and that memory traces do not decay over time, contributing equally regardless of location. The summary of parameters homogeneous to all agents and prescribed by researchers and heterogenous parameters that differ from agent to agent is put in Table 12.

Table 12 Notation, Explanation, and Values of Model Parameters

Notation	Explanation	Value
Homogeneous		
α_{sign}	Utility parameter of sign	1
α_{diff}	Utility parameter of room number difference	15
α_{seq}	Utility parameter of room number sequence	1
γ_1	Base of area familiarity discount	e
γ_2	Base of action familiarity discount	e
c_1	Increment of area familiarity	1
c_2	Increment of action familiarity	1
Heterogeneous		
Iso_{dist}	Visual perception distance	5-10 m
Iso_{range}	Visual perception range	90-120 degrees
W_c	Weight of spatial configuration	0-0.5
W_r	Weight of room number	0-0.5
W_s	Weight of directional guidance	0.5
W_{seq}	Weight of room number sequence	0-1
W_{diff}	Weight of room number difference	0-1

While these assumptions do not fully capture the complexity of real-world human behavior, they serve as a necessary foundation for systematic analysis. Beginning with a simplified and interpretable model allows for the isolation and understanding of core behavioral mechanisms before introducing additional layers of complexity. Incorporating too many variables prematurely risks obscuring key insights, reducing model transparency, and complicating validation. A stepwise approach ensures that each added component is both meaningful and empirically justified.

7.4 Results

7.4.1 Sensitivity Analysis

For all outcome measures, the ranking of variables regarding their main effect mu star is the same. Weight of spatial configuration (W_c) has the highest and dominant mu star values, followed by visual distance (Iso_dist), visual range (Iso_range), and weight of room number

Figure 37 Morris Indices of Three Outcome Measures for All Tasks

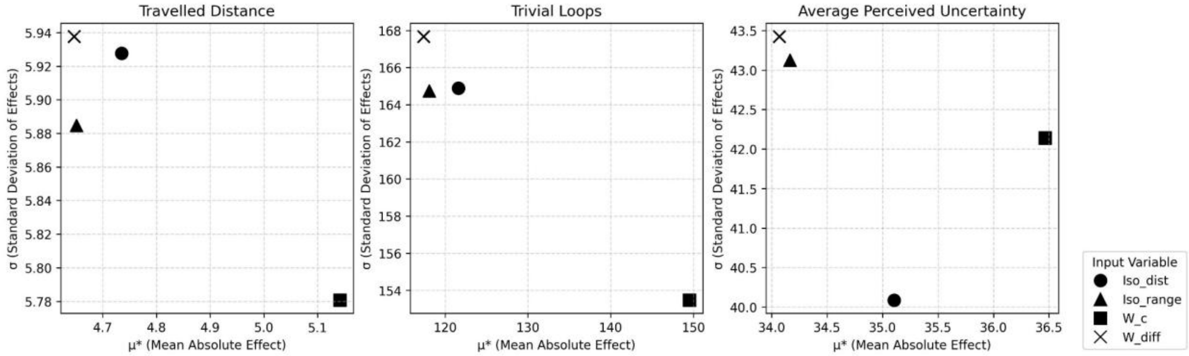
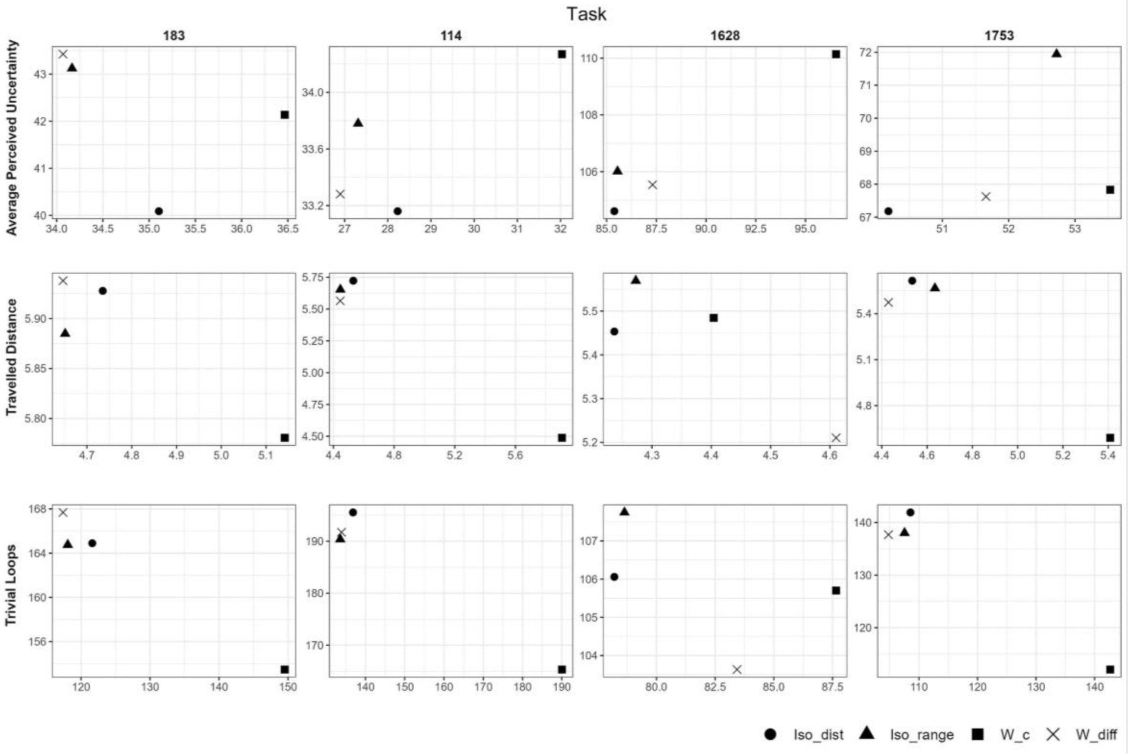


Figure 38 Morris Indices of Three Outcome Measures of Each Task



difference (W_diff). Visual distance has a bigger impact on average perceived uncertainty compared with the other outcome measures Figure 37.

Regarding variability, sigma rankings are similar for Travelled Distance and Trivial Loops, and W_c has the lowest sigma value, implying its impact on outcome measures is consistent. However, for the Average Perceived Uncertainty, W_c has a higher non-linear effect, and Iso_dist has the lowest sigma value.

We analyzed the Morris indices in different wayfinding tasks and observed a consistent strong main effect from W_c except in task 1628, where W_diff becomes the important factor when determining travelled distance and trivial loops. Visual range appears to be the less impactful factor for all outcome measures except for determining the average perceived uncertainty in task 1753 (Figure 38).

7.4.2 Behavioral Validation

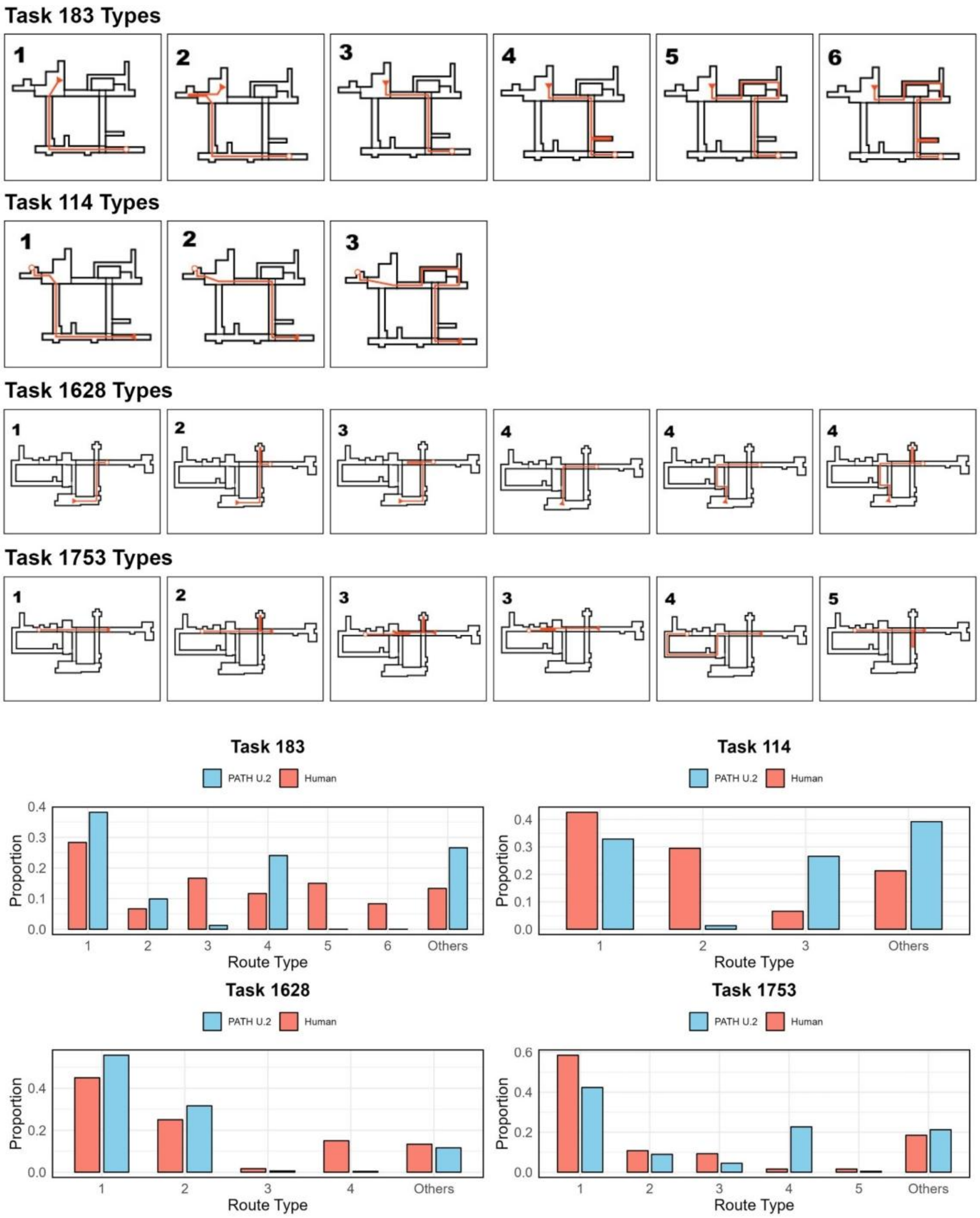
We classified six distinct route types for Task 183, three for Task 114, four for Task 1628, and five for Task 1753. The PATH U.2 agent was able to replicate all other human route sequences under specific parameter combinations except for route types 5 and 6 in Task 183, This demonstrates the model's capacity to reproduce diverse human route choice behaviors. The proportions of different route types taken by PATH U.2 agents and human participants are shown in Figure 39.

To better understand how different parameter settings lead to specific route types, we examined the PATH U.2 agent's route type distribution in 2D projections of the four-parameter space. The results revealed highly nonlinear relationships and clear interactions among visual distance, visual range, weight of spatial configuration, and weight of room number difference in shaping route choices. For example, in Task 183, agents selected route type 1 only when the visual distance exceeded 7 meters (Figure 40). This threshold allowed the agent to perceive room numbers farther down the corridor, making the left side appear attractive. In contrast, when visual distance was low, the spatial difference between left and right paths was less distinguishable. Route type 2 only occurred when the weight of spatial configuration was high, prompting agents to explore a small open area on the left before entering the main corridor. Furthermore, the PATH U.2 agent replicated both route types 3 and 4. These two types differ primarily in whether the agent explored the dead-end corridor containing room 180 before reaching the final destination at room 183. The agent exhibited similar exploratory behavior unless the weight of spatial configuration exceeded a specific threshold, discouraging deviation from the main path.

Similar replication of fine-grained human behaviors was observed across other tasks. In Task 114, the agent reproduced both major initial route choices, including the less frequent choice to explore a narrow corridor (Figure 41). In Task 1628, the complexity arose from an intersection presenting conflicting spatial cues—spatial layout, room number sequence, and differences before the destination (Figure 36). The PATH U.2 agent successfully replicated human route types 1, 2, and 3 (Figure 42). In Task 1753, a particularly confusing room number 1770 appeared after participants had passed rooms 1756 and 1755, often leading human participants to backtrack and explore unfruitful areas. The agent reproduced this behavior when the weight of room number difference was set below approximately 0.25 (Figure 43).

We also examined the “Others” category, which includes unclassified or irregular behaviors. PATH U.2 agents were able to replicate typical “lost” behavior under certain parameter combinations, such as repetitive back-and-forth movement within a corridor after both

Figure 39 Route Types of Each Task and The Proportion of Their Occurrences



ends had been explored. In large open areas lacking directional cues, the agents, like human participants, tended to wander for a longer period before committing to a route choice. The agents also demonstrated backtracking behavior when approaching previously visited areas.

These results collectively demonstrate that the PATH U.2 framework can replicate the majority of human route types and capture fine-grained, dynamic interactions between spatial configuration and room number information. They also highlight the complexity and nonlinear nature of real-world wayfinding tasks, where small variations in spatial configuration or individual differences in information weighting can lead to substantially different route choices and navigation outcomes.

Figure 40 Route Type Distribution for Task 183 in 2D Projections of the Four-Parameter Space

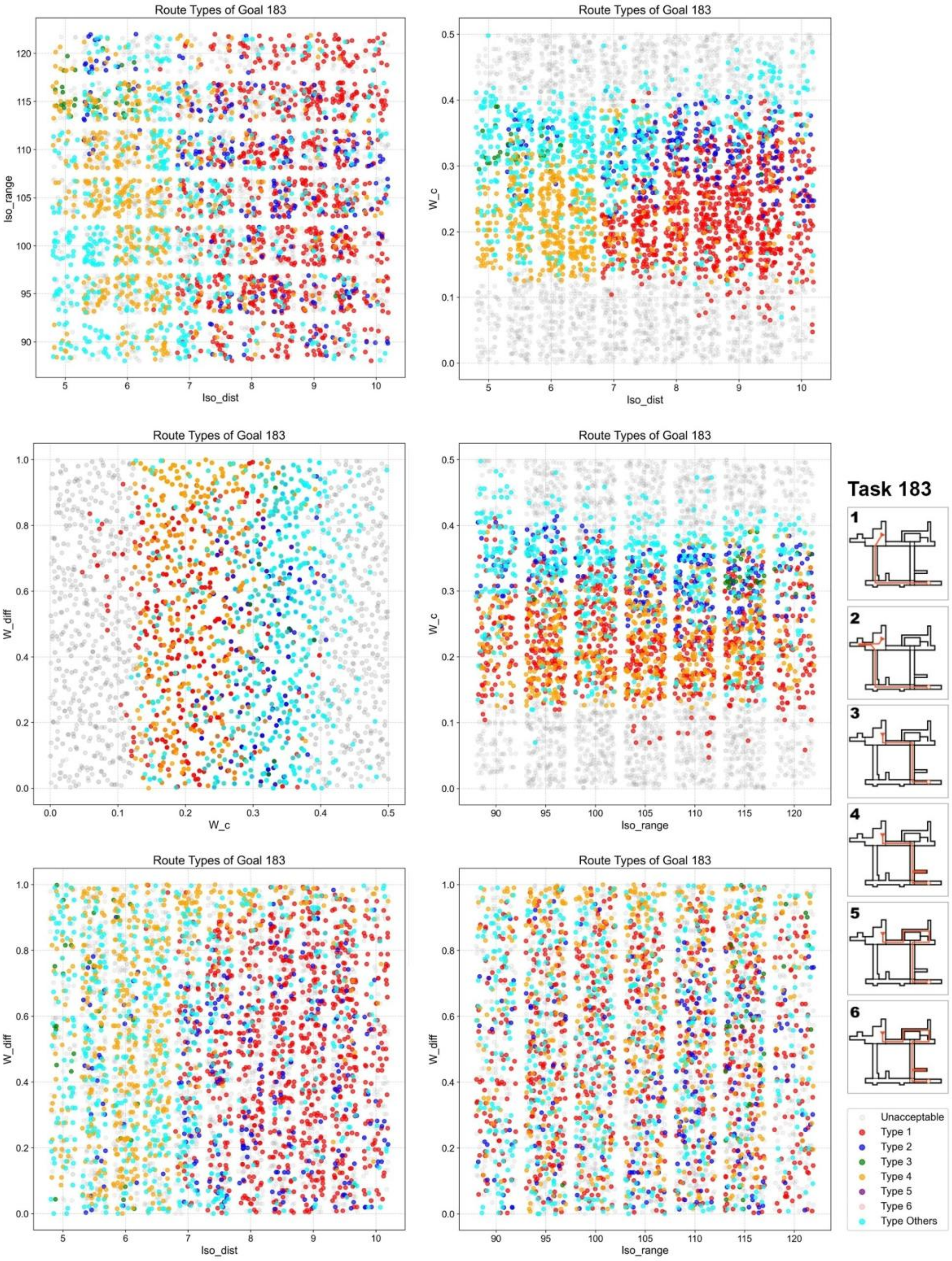


Figure 41 Route Type Distribution for Task 114 in 2D Projections of the Four-Parameter Space

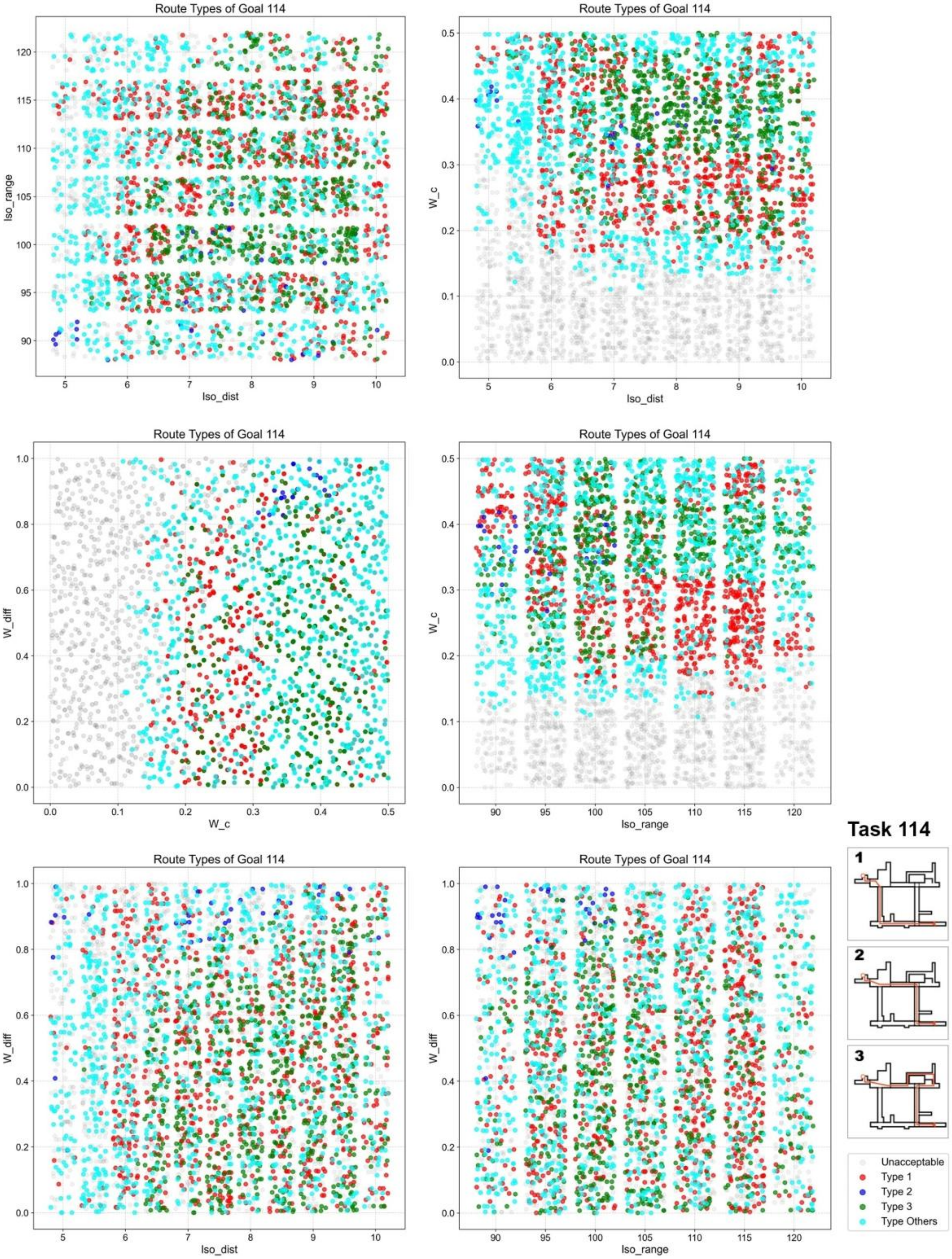


Figure 42 Route Type Distribution for Task 1628 in 2D Projections of the Four-Parameter Space

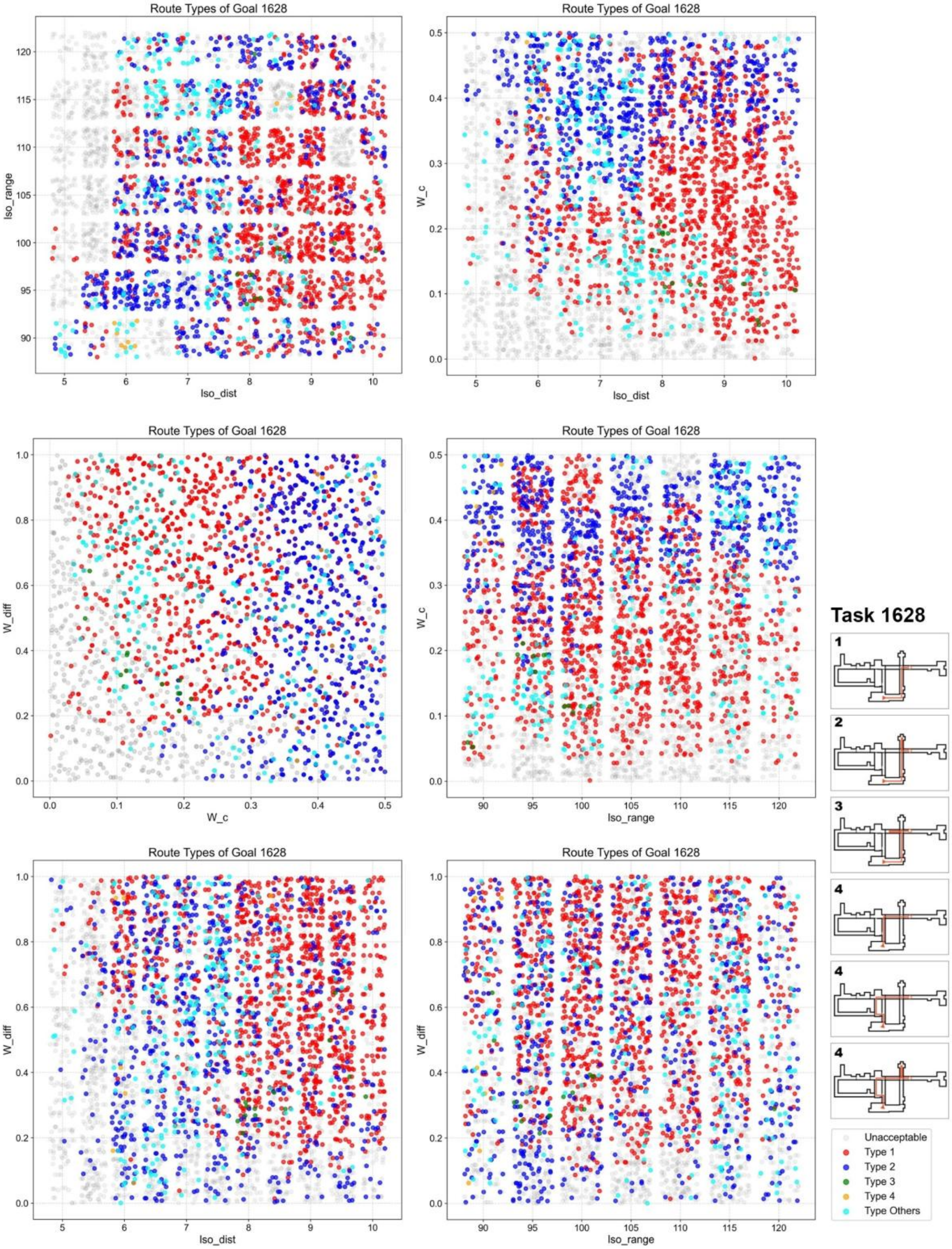
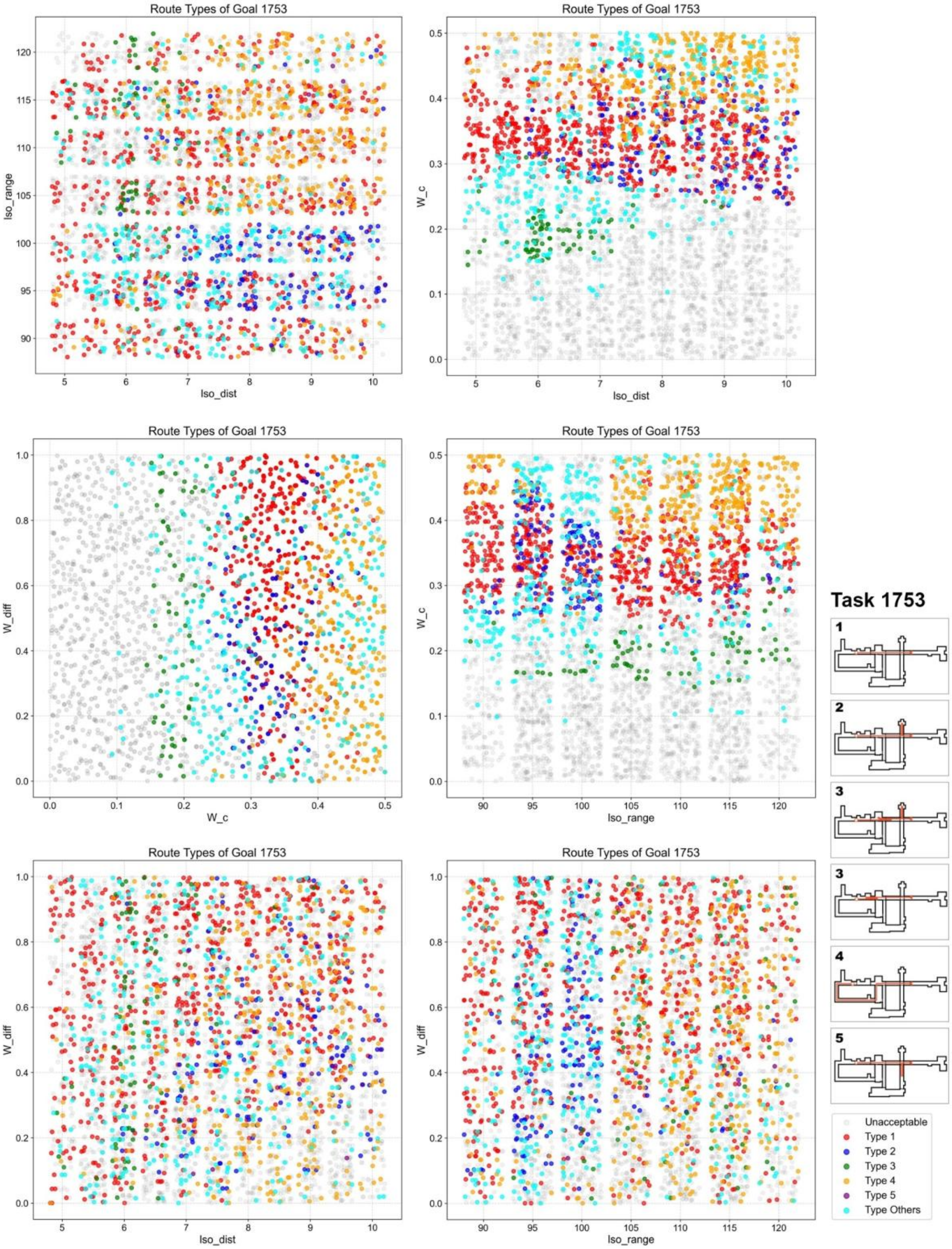


Figure 43 Route Type Distribution for Task 1753 in 2D Projections of the Four-Parameter Space



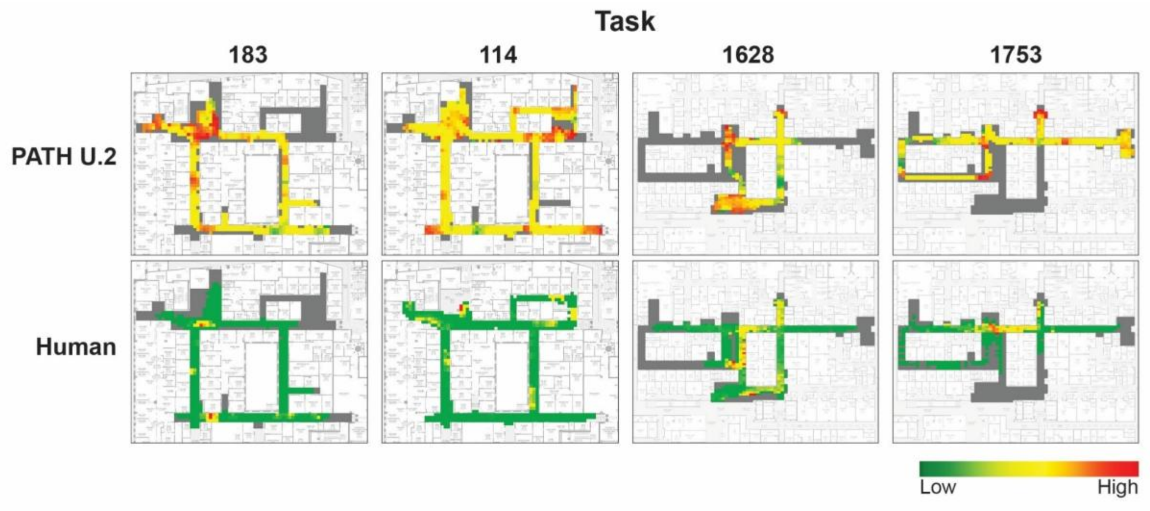
7.4.3 Performance-Travelled Distance

The PATH U.2 agent demonstrated significantly more accurate predictions of average travelled distance compared to the shortest-path agent based on the A* algorithm (Figure 44). Despite a similar distribution of route types to human participants, the PATH U.2 agent consistently traveled slightly longer. Notably, in Task 1753, the discrepancy between the PATH U.2 agent and human participants was larger than in the other three tasks (Table 13). The analysis and explanations will be presented in the discussion section.

Table 13 Mean and Confidence Interval of Human, PATH U.2 Agent, and A Agent*

Task	Type	Mean (meter)	Confidence Interval
183	Human	71.7	[64.9, 78.6]
	PATH U.2	88.1	[78.4, 97.8]
	A*	41.5	\
114	Human	81.5	[69.1, 93.9]
	PATH U.2	90.6	[80.6, 95.3]
	A*	48.9	\
1628	Human	72.6	[59.2, 86.0]
	PATH U.2	87.9	[80.6, 95.3]
	A*	37.3	\
1753	Human	70.1	[60.9, 79.3]
	PATH U.2	114.8	[105.8, 123.7]
	A*	34.2	\

Figure 44 Comparison of Travelled Distance by Task from Human, PATH-U.2 Agent, and A Agent*

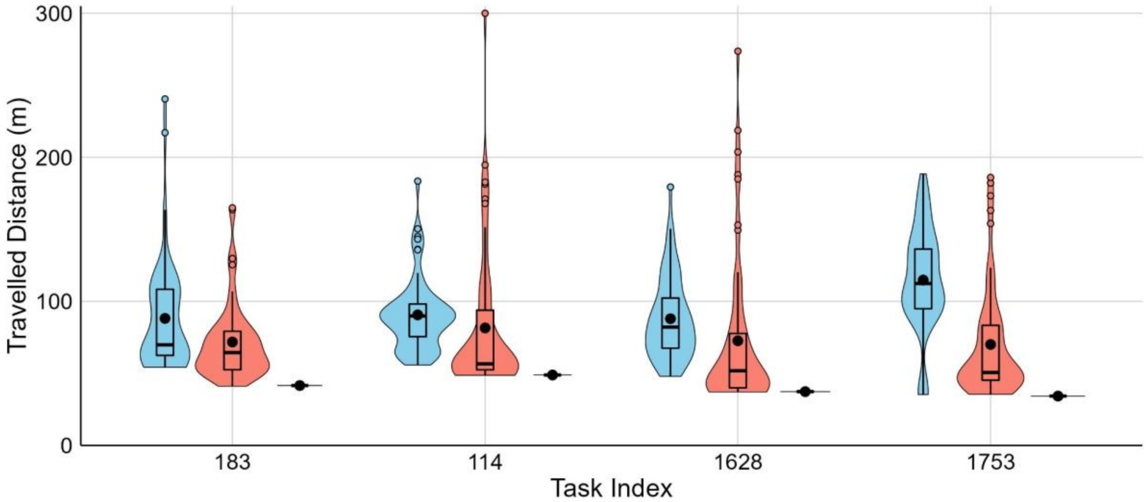


7.4.4 Performance-Perceived Uncertainty

The fine-grained spatial distribution of perceived uncertainty between human participants and the PATH U.2 agent reveals both notable similarities and key discrepancies, as observed through visual inspection. The agent effectively captured several instances of human-reported uncertainty arising from unintuitive room number systems (Figure 45). For instance, in Task 183, the agent accurately identified an area of high uncertainty located in the middle of the corridor—an area that human participants also found confusing due to non-sequential room numbering. The agent also detected uncertainty at corridor intersections where participants encountered rooms 142 and 188 while searching for room 183, which may have led them to believe they had missed the destination or entered an irrelevant area. Similarly, in Task 1753, the agent correctly identified an uncertain spot triggered by the appearance of room 1770 following rooms 1756 and 1755, a sequence that confused many human participants.

Beyond room number confusion, the PATH U.2 agents also successfully predicted high uncertainty in large open spaces with multiple branching paths, such as the starting areas in each

Figure 45 Spatial Distribution of Perceived Uncertainty Between PATH U.2 Agent and Human



task. In the absence of clear signage or room number cues, these locations presented equally viable directions, resulting in high decision entropy and uncertainty for both agents and humans.

However, discrepancies between agent and human uncertainty estimates were also observed. Specifically, the agents frequently identified dead-end corridors as uncertain areas, while human participants did not report such areas as confusing, leading to false positives. Additionally, agents tended to exhibit a higher baseline level of perceived uncertainty compared to humans, likely due to the inherent properties of the entropy-based uncertainty algorithm used in the model.

To further evaluate predictive accuracy, we aggregated perceived uncertainty by spatial zones and compared the zone-level rankings between humans and PATH U.2 agents. While the agent achieved relatively strong performance in Tasks 114 and 1753—demonstrated by the

Figure 46 (A) Decision-making Zones of Two Areas (B) Average Perceived Uncertainty by Zone

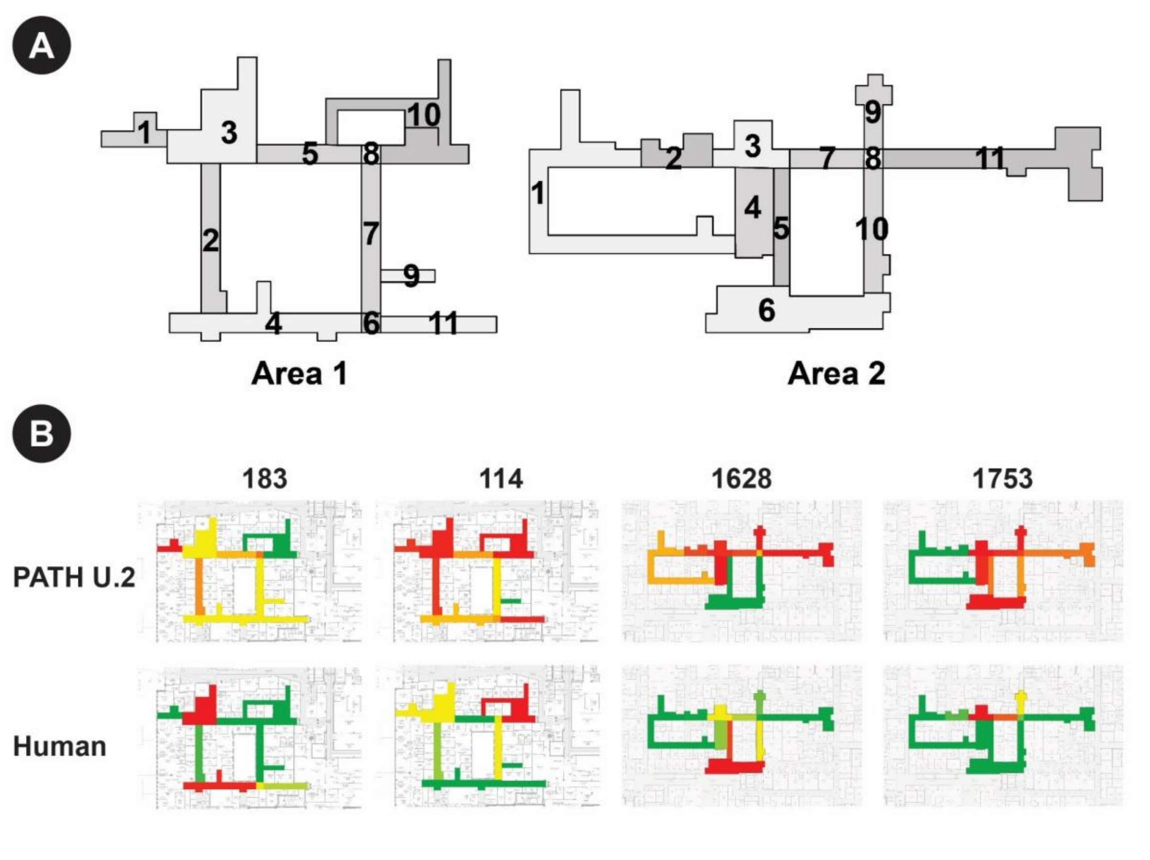
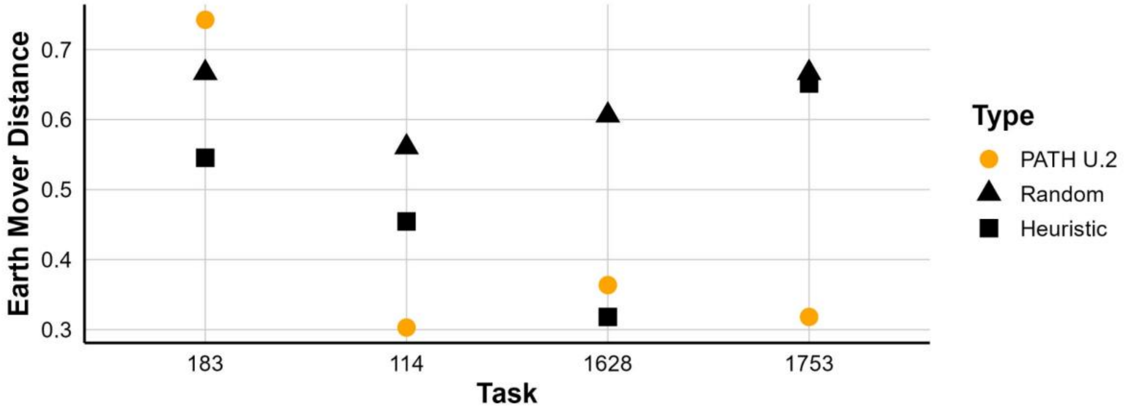


Figure 47 Earth Mover Distance Between PATH U.2, Random, and Heuristic Agents and Human



lowest Earth Mover's Distance (EMD) values—it did not outperform a simple heuristic zone-ranking method in Task 1628, and performed the worst in Task 183. This occurred despite the agent's success in identifying localized uncertain spots in Task 183, suggesting a mismatch between fine-grained predictions and broader zone-level patterns in certain contexts (Figure 46B and Figure 47).

7.5 Discussion

The PATH U.2 model demonstrates diverse and realistic human route choice behaviors through a succinct computational representation of wayfinding in unfamiliar indoor environments. It extends existing models such as CogArch, which focuses on semantic task-based navigation (for example, finding a café), by introducing a more comprehensive utility-based framework that supports number-based tasks [193]. Specifically, PATH U.2 integrates spatial configuration, directional cues, and room number reasoning to model agent decision-making. Compared to earlier models of sign-guided navigation, including the original PATH-U that primarily checks whether a destination appears on signage, PATH U.2 enhances the representation of guided wayfinding by incorporating room number heuristics and utility functions for two types of reasoning: numerical difference and sequence inference. By formalizing these reasoning processes, PATH U.2 successfully replicates 16 out of 18 dominant human route types, underscoring the model's validity in capturing core patterns of human wayfinding behavior.

The sensitivity analysis shows that all parameters are necessary. The weight assigned to spatial configuration plays the most significant role in determining agent route choice behavior. In most tasks, assigning excessive weight to either spatial configuration or room number reasoning results in less acceptable trajectories, as the agent relies on a single source of information, which leads to less robust decision-making. Although the relative weight of sequence reasoning versus numerical difference appears to have less impact overall, it does influence behavior in specific tasks such as Task 1628. This task includes an intersection where the agent must reason with conflicting information derived from sequence and numerical difference. Therefore, despite the dominant influence of spatial configuration, the other three parameters remain essential for achieving realistic and adaptive wayfinding behavior.

Whereas most existing simulations assess model performance solely based on total traveled distance, PATH U.2 advances the field by providing fine-grained, moment-to-moment predictions of perceived uncertainty. This allows designers to better identify locations that induce confusion and manage user uncertainty more effectively. We argue that models offering such temporally and spatially detailed feedback not only increase ecological validity but also enable deeper insights into the dynamic, fine-scale interactions between humans and built environments.

The model is grounded in cognitive theory, using the entropy formula to represent psychological uncertainty [3]. Empirical data further support its validity: predictions from the entropy-based model align with human uncertainty experiences in several key decision-making areas. These results suggest that the model effectively captures the distribution of utility across directional choices and supports the theoretical application of entropy model to wayfinding uncertainty.

Nonetheless, several discrepancies between PATH U.2 and observed human behaviors remain. For example, in Task 183, the model fails to reproduce Route Type 5. Upon closer analysis, this discrepancy arises because the agent does not account for closed but unlocked doors, which are commonly found in healthcare settings. These doors reduce the perceived accessibility of certain routes for human users and often lead them to choose narrower paths that the agent, based on its current algorithm, tends to avoid. As a result, humans often choose narrower but more accessible routes, which the agent avoids based on its current algorithm. A similar issue appears in Task 1628, where the agent prefers to move from Zone 5 to Zone 4 rather than continuing straight within Zone 5. This suggests that door affordances, and potentially other environmental cues such as windows, furniture, and color, can influence human wayfinding but are not yet included in the current agent framework.

Another notable discrepancy is seen in Task 1753. Only three participants explored the far end of Zone 11 before heading toward Zone 8, whereas most PATH U.2 agents began by exploring the right side of Zone 11, resulting in substantially longer paths. This difference stems from the participants' prior exposure to the environment: many had already encountered room number 1758 in Zone 7 during the previous task (Task 1628). This familiarity led them to proceed directly toward Zone 7 in Task 1753. Such findings highlight a limitation in the data collection process and emphasize human sensitivity to spatial memory. These observations point to the need for more sophisticated memory modeling when it is unrealistic to assume participants have zero prior spatial knowledge.

Despite these limitations, PATH U.2 provides a robust, adaptable, and scalable computational framework. By holistically integrating environmental abstraction, visual perception, cognitive reasoning, utility-based decision-making, and perceived uncertainty quantification, the model offers a strong foundation for future research. For future researchers, its modular architecture allows for easy extension and customization to improve behavioral realism across diverse wayfinding contexts and populations. Beyond its theoretical contributions, PATH U.2 serves as a powerful tool for testing and optimizing signage systems. By simulating pedestrian navigation under diverse conditions, the model can identify wayfinding bottlenecks, highlight areas prone to user confusion, and pinpoint locations where additional signage or clearer directional cues are necessary. This capability offers significant value to urban planners, architects, and transportation designers, enabling the strategic placement of signs, improved legibility, and enhanced overall efficiency of navigation systems in complex environments.

7.5.1 Future Works

Several assumptions in the current model may not fully reflect real-world wayfinding behavior and could be improved through further refinement. For example, humans experience sensory uncertainty and do not have perfect visual perception, which can lead them to overlook signs or even miss destinations. Besides, information gain is not uniform within the visual catchment area; instead, it is influenced by both visual angle and distance. Such perceptual behaviors have been examined in prior studies [109] and could be integrated into the model to enhance its realism.

Additionally, people often exhibit inertia when changing direction in the absence of new information, a tendency commonly described as the "follow-the-nose" heuristic [235]. When multiple corridors are accessible from an open space, the one closer in proximity may appear more appealing. These subtle affordances related to accessibility warrant further investigation and could be modeled within the utility function to simulate more realistic human preferences.

The current memory trace component could also be expanded to better represent memory-dominated wayfinding. Salient environmental features tend to enhance memory encoding and could be modeled by varying the intensity of memory traces. A more advanced approach would involve simulating the internal representation of the environment and how it evolves during initial exposure. Prior research has proposed comprehensive representations for specific micro-scale wayfinding tasks [93] and examined memory distortion effects [91]. A memory model for building-scale wayfinding tasks during first-time visits could significantly improve the realism of simulations in unfamiliar settings.

Social interaction and crowd dynamics are also known to influence wayfinding behaviors. The current PATH U.2 framework provides a basis for incorporating the utility of social interaction as an additional variable. However, formalizing utility gained from observing others' movements remains an open area for investigation. Studying the dynamics of multi-agent interaction could offer valuable insights into socially informed wayfinding.

Furthermore, the utility function associated with spatial configuration in PATH U.2 could be enhanced through data-driven approaches or by integrating large language models. Although isovist area has proven effective in the current wayfinding tasks, environmental cues that influence human behavior can differ significantly across building types. Translating these cues into meaningful utility values often requires complex reasoning. Empirical datasets evaluating go-to affordance, combined with data-driven modeling, may improve the model’s adaptability and accuracy. Additionally, incorporating reasoning capabilities from large language models holds promise, but such integration must be carefully validated to ensure reliability and alignment with human cognitive patterns.

It is also common in wayfinding models to define two psychological states related to navigation: a state of calmness and a state of anxiety/panic [111]. Individuals experiencing heightened uncertainty may engage in markedly different behaviors, including anxious navigation or cautious exploration. With PATH U.2's ability to compute perceived uncertainty, future studies could explore thresholds that trigger these psychological states and how they influence decision-making.

With PATH U.2 validated, an immediate next step is to conduct scenario-based explorations across varied layout typologies and signage placements. These simulations could examine failure modes and performance across diverse user populations. For example, can the model provide insights into effective wayfinding heuristics and signage strategies? How does performance change when wayfinders have limited memory or miss a destination? Does the building afford opportunities for recovery from such errors? Individual differences in spatial ability and tolerance for uncertainty also require attention. Simulating users with lower uncertainty tolerance may help identify environments that unintentionally induce anxiety and support more inclusive design strategies.

7.6 Conclusion

This study presents PATH U.2, a cognitive agent model that simulates realistic human wayfinding behaviors in unfamiliar indoor environments. PATH U.2 introduces a utility-based framework that integrates memory, spatial configuration, directional cues, and room number reasoning to support diverse and human-like route choices. Validated using an empirical wayfinding dataset involving 69 participants in a physical healthcare environment, the model successfully replicates a broad range of observed human trajectories and generates fine-grained predictions of perceived uncertainty. These capabilities contribute both behavioral realism and diagnostic value for spatial design. The validation results show strong alignment between PATH U.2 and human navigation patterns across multiple tasks. Although some discrepancies persist, particularly in capturing environmental affordances and prior spatial memory, the model's scalable architecture and cognitive foundation offer a solid basis for future refinement and extension. PATH U.2 not only advances wayfinding models in unfamiliar environment but also offers practical implications for designing more navigable and inclusive built environments.

Chapter 8. Conclusion and Future Research Directions

This dissertation advances wayfinding research by introducing and validating a continuous measure of perceived uncertainty that complements existing task-level instruments. Using this measure, I conducted virtual reality experiments with high-resolution behavioral and cognitive data to map how rhythms of information gain shape uncertainty, curiosity, anxiety, and decision making. The empirical findings highlight the complex, dynamic nature of perceived uncertainty in unfamiliar environments and its influence on wayfinding behaviors.

Building on these insights, I translated empirical evidence and cognitive theories into two computational models. Among them, PATH U.2 offers a succinct, scalable framework capable of predicting wayfinding performance and moment-to-moment uncertainty with high spatio-temporal resolution. This model was empirically validated using real-world data from healthcare settings, incorporating finer-grained metrics such as route types that are often overlooked. Model simulations further expose the complexity of wayfinding: small variations in individual traits or seemingly minor environmental features, such as the placement of a single door, can redirect route choices and produce markedly different trajectories.

Methodologically, the dissertation contributes novel research approaches to the field, including the use of VR for controlled yet ecologically valid experimentation, and response surface analysis to reveal not only how environmental variables influence wayfinding behavior but also how it matters.

Overall, this work offering new theoretical, methodological, and computational tools to better understand and simulate human navigation in unfamiliar built environments.

8.1 Future Research Directions

Building on the findings of this dissertation, several promising directions for future research emerge.

First, to deepen our understanding of human wayfinding behavior and provide empirical data essential for validating behavioral models, it is necessary to develop novel methods for large scale, high spatio-temporal data collection. This includes leveraging indoor sensing technologies capable of capturing accurate, participant-specific trajectories, as well as designing web-based wayfinding games or virtual platforms that meaningfully approximate real world navigation experiences. Researchers have successfully developed wayfinding-related games such as Sea Hero Quest [229]. While such games offer insights into the cognitive mechanisms underlying navigation, they often rely on fictional environments and tasks, limiting their ability to reveal how humans interpret and respond to real world environmental features. As a result, their external validity is reduced, providing less actionable insight for environmental designers.

Second, current methods for capturing human experiences such as perceived uncertainty remain limited. Future research should investigate whether behavioral and physiological signals such as head movements, blinking, sweating, and EEG can reliably serve as proxies for perceived uncertainty. If self-reporting remains necessary, wearable interfaces such as AR glasses, smartwatches, or e-textiles could facilitate more scalable and naturalistic data collection.

A deeper examination of the cognitive and affective dynamics of uncertainty is also warranted. For instance, it remains unclear under what conditions uncertainty triggers curiosity rather than anxiety. This may depend on the source or type of uncertainty, including perceptual, state, rule-based, or outcome uncertainty. From a design perspective, future work could experimentally determine the thresholds at which uncertainty motivates exploration versus avoidance, and how these thresholds vary across individuals and contexts. Such insights could inform models of human behavior and guide the design of environments that optimize wayfinding performance while preserving the value of spatial curiosity and serendipitous exploration.

Similarly, backtracking behavior presents a rich but underexplored window into decision making under uncertainty. Understanding the thresholds of uncertainty tolerance that trigger withdrawal or backtracking is crucial. In our empirical study, backtracking exhibited dual effects, sometimes reducing inefficient exploration, but at other times leading to superficial searching and significantly prolonged task completion. It is also plausible that certain rhythms or temporal patterns of uncertainty are more likely to induce backtracking. For example, a particularly confusing entrance experience may reshape one's expectations of the building and result in maladaptive wayfinding strategies, even if the overall layout is not inherently complex.

Another compelling direction involves examining how spatial schemas and prior assumptions about architectural features influence navigation, and what types of interventions might help individuals revise or override these assumptions. Predictive brain theory suggests that the brain continuously generates predictions based on prior knowledge and adjusts them through feedback. Even when individuals are unfamiliar with a specific building, they still hold priors about its function and environmental features, which shape their initial wayfinding expectations. Although heuristic decision-making strategies in wayfinding have been studied, limited work has addressed how established spatial schemas and prior expectations form, and more importantly, how they can evolve over time.

Future directions for computational modeling and simulation of human wayfinding could address several open challenges revealed through this dissertation.

First, the model's ability to predict perceived reward from spatial configurations requires significant improvement. While current models, including PATH U.2, approximate local reward through a combination of spatial configuration, signage, and room numbering and achieve believable behavioral outcome, the information gain is calculated solely based on visual catchment areas. This simplified approach may suffice in controlled environments but can be inadequate in more complex architectural settings. Incorporating a more sophisticated, potentially data-driven model could yield more generalizable and robust reward estimations.

Second, detailed sensitivity analysis of specific components such as isovist area based navigation and entropy driven uncertainty prediction remains to be conducted. These efforts could improve the transparency and interpretability of the model, increasing designers' confidence in its application.

Third, modeling information gain from spatial schemas during first-time navigation presents a valuable opportunity. The way people anticipate spatial layouts, and how these anticipations influence the interpretation of environmental features, is not yet well understood or formally represented computationally.

Fourth, modeling imperfect cognitive formation, particularly the incomplete or inaccurate development of cognitive maps during first-time navigation, is a significant challenge. Many existing models assume perfect memory or immediate integration of spatial knowledge, which overlooks the gradual and error-prone nature of environmental learning. This study introduces a plausible approach for modeling memory encoding, which can be further refined to reflect the effects of imperfect memory on local decision making.

Finally, with a more cognitively grounded and believable model, future research can evaluate architectural layouts and room number arrangements to test and go beyond existing design heuristics. Simulation based scenario exploration can reveal how specific design choices may lead to severe wayfinding failures, allowing designers to identify and prevent such outcomes before implementation.

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