An Evidence-based Cognitive Model of Human Wayfinding under Uncertainty

QI YANG*, ROHIT K. DUBEY*, and SALEH KALANTARI

Wayfinding - the process of goal-directed planned movement in an unfamiliar, large, and complex environment is challenging and often executed under uncertainty. Wayfinding uncertainty is a mental state experienced, especially in an unknown environment, when deciding between two or more competing route choices at a decision point. Even though uncertainty is intrinsic and plays a crucial role during wayfinding, the existing computational model of human wayfinding provides no or minimal support for modeling uncertainty during wayfinding. Therefore, it is paramount to incorporate uncertainty into a wayfinding model to produce realistic human wayfinding. In this paper, we ground the wayfinding process on the concept of oriented search (as proposed by Allen (1999)), employing directional information from signage and spatial layout. We model the two most common and prevalent uncertainty during wayfinding: (1) Route-choice uncertainty: Originates when an occupant is at a decision point and has to select a route out of the multiple route choices. (2) Affirm on-route uncertainty: Originates when an occupant is in-between decision points (e.g., a long corridor, large open space) and tries to ascertain if its current location is on the correct route towards the destination. We model route-choice uncertainty as a function of two attributes: the number of possible outcomes and the probability distribution of belief in electing each outcome at a decision point. We conducted a real-world experiment with XX participants to parameterize and validate the wayfinding uncertainty model. After preliminary analysis of the collected and simulated data, we observe similar wayfinding behavior between simulated agents and participants regarding perceived continuous uncertainty during wayfinding and route-choice behavior at decision points.

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1 INTRODUCTION

Wayfinding - the process of goal-directed planned movement in an unfamiliar, large, and complex environment is a challenging task. An occupant's movement can be modeled as a sequence of possible route choices at decision points (e.g., intersections) that (s)he needs to select under uncertainty. Wayfinding uncertainty is a mental state experienced, especially in an unknown environment, when deciding between two or more competing route choices at a decision point. According to Allen (1999), people rely on a multitude of wayfinding means and strategies to accomplish a wayfinding task depending on external and internal information. The degree of wayfinding uncertainty depends on the availability of visual and spatial cues assembled during locomotion and past familiarity of the place. For example, uncertainty will be high when an occupant is confronted with a route-choice decision at an intersection without directional aid such as signage or a landmark in an unfamiliar building. Wayfinding uncertainty though not limited to the below list largely arises due to the following reasons: (1) It can arise when one tries to orient oneself (e.g., coming out of a transit hub and trying to orient oneself with something known such as a landmark). (2) While planning a route towards a destination

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among mutiple possibilities. (3) Uncertainty can arise if there is a discrepancy in route instruction via a navigation app or human interaction. (4) Finally, uncertainty can arise due to the environment when either a landmark or other forms of visual cues becomes imperceptible.

Even though uncertainty is intrinsic and plays a crucial role during wayfinding, the existing computational model of human wayfinding provides no or minimal support for modeling uncertainty during wayfinding. Few recent research has started to focus on modeling uncertainty in wayfinding. Jonietz et al., [Jonietz and Kiefer 2017] provided a computational model of uncertainty resulting from non-deterministic reference system transformations in various wayfinding scenarios comprising agent, environment, and route instruction. Their work focuses primarily on instruction-based wayfinding situations where uncertainty arises due to the mismatch of route instruction, resulting in ambiguity in selecting a route due to non-deterministic spatial reference system transformation. For example, ambiguity can arise from a route instruction such as "select a route in front of a yellow postbox" in an environment where two or more non-tangential route choices are available nearby a yellow postbox.

Removing wayfinding uncertainty, even in a properly constructed environment with sufficient wayfinding cues, is improbable. Due to human cognition, uncertainty will likely arise in most wayfinding scenarios. Therefore, it is essential to incorporate uncertainty into a wayfinding model to produce realistic human wayfinding. In this paper, we ground the wayfinding process on the concept of oriented search (as proposed by Allen (1999)), employing directional and destination signs on the wall or attached to a panel. We propose to model the second tenet of Hirsh et al., entropy model of uncertainty (EMU) [Hirsh et al. 2012] that says: "uncertainty emerges as a function of the conflict between competing perceptual and behavioral affordances". The focus of this paper is to model the most fundamental form of uncertainty in wayfinding (i.e., route choice uncertainty) that arises due to the mismatch or lack of environmental and wayfinding cues in an unfamiliar building. Specifically, we aims to model occupant's uncertainty, such as: "am I on the correct path while walking on a long unaided corridor" and uncertainty that arises while selecting a route at an intersection that contains multiple route possibilities with none of the route options outweighs the other with a significant selection margin. To the best of our knowledge, no research has explicitly incorporated the route-choice uncertainty in a human-wayfinding model.

2 RELATED WORKS

Multiple conceptual frameworks have been proposed to model navigation processes and relevant cognitive processes. However, limited simulation studies have tried to model the stochastic and non-linear nature of human wayfinding process, and validate the results with empirical data. Some methods to model human behavior include defining events that trigger specific narratives and actions of different types of agents [Schaumann et al. 2019], or transforming known wayfinding heuristics into rule-based deterministic algorithms [Gath-Morad et al. 2020]. By prescribing behaviors and strategies, those methods could probably offer simulation of complex environment-human interactions, but more realistic and generalizable wayfinding behavior simulations requires the articulation of how information is transformed into decisions and how decisions affect information in return. One early theoretic work by Raubal described wayfinding as iterating loops of perception, decision and actions [Raubal 2001]. To simulate realistic perception process, some studies developed agents that can visually perceive signs like human and act according to the instructions on the signs [Dubey et al. 2021][Becker-Asano et al. 2014]. Besides signs, computational cognitive models for landmark recognition was proposed [Dubey et al. 2019b]. Another study modeled utility of wayfinding uncertainty based on traveled distance, direction toward the destination and landmarks [Najian and Dean 2017]. Similarly, other studies modeled route-choice as rational decision-making processes [Chen 2012][Bode et al. 2014]. Those studies provided necessary computational components for the cognitive wayfinding agent. Combining visual perception of signs, search behavior and motion planning, Maruyama created a wayfinding agent that could identify "disorientation spot" and get lost [Maruyama et al. 2017]. Building Upon this study, our study contributed to more realistic wayfinding simulation in following ways: 1. We changed the information perception behavior to a stochastic process with empirical data. 2. We integrated back-tracking behavior into the simulation and developed the sign inference function that modeled the reward of the agent at each step. 3. We defined route-choice uncertainty and validated the uncertainty with real participants.

3 REAL-WORLD EXPERIMENT

To validate our simulation, one empirical study with forty participants was conducted in an educational building. All participants were not familiar with the environment. Each participant was asked to finish seven wayfinding tasks, during which they self-report perceived uncertainty using joystick in real time [citation], and their trajectories with timestamps were documented. On the simulation side, locations and information of all relevant signs were digitized and combined with the digital model of the building, which allow us to compare the performance with empirical data.

4 COGNITIVE MODEL OF WAYFINDING UNDER UNCERTAINTY

4.1 Preliminaries

In this section we ground the agent's visual perception model and explain the signage and environmental model used in the proposed computational framework. Both of which are very important for reproducing the results and performing realistic validation with real-human data. We employed the Unity3D game engine (https://unity3d.com/) to develop and simulate the agent movement behavior under uncertainty.

4.1.1 Agent Visual Perception Model. In wayfinding research, visual cues in the built environment are a human's primary source of distal information [Schinazi et al. 2016]. In order to realistically model the interaction between agents and their environment, a human-like visual perception model should focus on the first-person perception of signage while considering dynamic occlusions [Moussaïd et al. 2011]. We employ a simple version of the agent-signage interaction based wayfinding system that is inspired by vision-based wayfinding simulation using a cognitive agentsignage interaction model as described in [Dubey et al. 2021]. In our model, the horizontal field of view (FOV) is modeled to realistically simulate the agents' visual perception. The effective horizontal FOV is 120 degrees in order to account for human neck rotation [Fisher et al. 1987] during search behavior (i.e., before the sign is detected). Two physiological aspects of an occupant are embedded in the agent framework: occupants' eyesight and height. Occupants' eyesight is considered as near perfect with no defect in sight. Average eye height of 1.7m is considered for running the simulation. These parameters can be adjusted based on the population distribution of a building.

4.1.2 Signage and Environment Model. In the proposed model, a signage system consists of signs. Individual signs are represented by their directional attributes, along with a list of goal locations. Each sign is considered an asset, and the sign's property is assigned during its creation at the start of the simulation. A sign is visible when an agent is inside the sign's visual catchment area (VCA) and can see the sign without occlusion [Dubey et al. 2021]. A dynamic visibility check is performed to determine the latter. When an agent reaches an intersection (i.e., decision point), it begins looking for a sign. The agent proceeds towards the direction provided if a sign is detected with the destination information. In the absence of a sign or a failure to detect a sign, the agent selects a route that is computed using the proposed route-selection model under uncertainty (see Section 4.2). The environment is modeled as a directed weighted graph $G(N, E)$ with decision points (DP) as nodes N and available routes as edges E. DP are identified computationally based on the methodology suggested in [Dubey et al. 2020].

4.2 Simulating Natural Movement

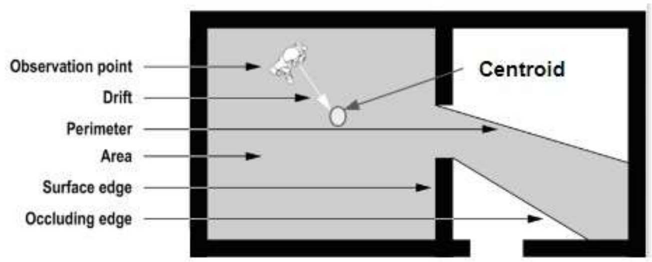

Fig. 1. Visualization of an agent isovist with drift measure. Place holder, image will be replaced

We propose a vision-based navigation model to simulate realistic human exploration in an environment. Mammalian navigation is a simple ecological behavior induced by an interaction between an agent and its environment. The purpose of this model is to simulate a natural movement without considering any particular destination as a target. In short, a general exploration model of an occupant inside a building.

We leverage the agent visual perception model that produces a 2D FOV by formulating a partial isovist. An isovist represents the local geometrical properties of spaces in a built environment from a specific vantage point. A partial isovist is a constraint form of a full 360-degree viewshed. Partial isovist captures a realistic human field of view by controlling the aperture angle of the viewshed. In a partial isovist, drift measure identifies the inherent 'flow' within a space, or the 'pull' or 'push' an occupant might feel from the spatial layout influence. Drift is the distance between the location from which the isovist is cast (i.e., an agent eye location) and its centroid [Dalton 2003] (see Figure 1). Drift has a direction which is a vector pointing towards the centroid of a partial isovist. In our model, we simulate agent movement by making the agent continuously move towards the drift location. This process is cyclic as agent movement dynamically changes the drift position, pulling the agent forward.

4.2.1 Agent's Internal Information. It is well established that humans employ prior beliefs, strategies, and heuristics to complete the wayfinding task when in doubt. For example, suppose the direction to the destination is known. In that case, most humans apply the least angle heuristic at decision points (i.e., selecting a route with the least deviation from the perceived destination direction). Tenbrink et al. present a comprehensive list of wayfinding heuristics, and we guide the reader to [Tenbrink and Wiener 2006]. To maintain the similarity to the conducted experiment (see Section ??), We propose to model the following prior belief and heuristics into the proposed cognitive agent.

- Floor strategy (S1): First, find the way to the destination floor, irrespective of the horizontal position of the goal [Hölscher et al. 2005]. In an unfamiliar environment, the agent infers the floor level by matching the destination room number with the room numbers and signage observed during wayfinding.
- Following continuously marked signage/room numbers (S2): Humans try to minimize the distance to the destination by following the direction provided by the indirect visual cues that minimize the distance to the destination Allen (1999).
- When in doubt, follow your nose (S3): In an unfamiliar environment, when people are in doubt, it has been observed that they follow as straight a route as possible with minimal angular deviation (from a straight line) [Dalton 2003; Meilinger et al. 2014].

In Section 4.2, we explain in detail how we model the above described heuristics into our cognitive agent. This closely represents the "belief" in the widely-used belief-desire- intention (BDI) framework [Rao et al. 1995]. To the best of our knowledge, this is the first attempt to incorporate the well-grounded heuristics mentioned above in a computational wayfinding model. The role of scene memory (i.e., short-term memory of environment during wayfinding task) is deliberately not considered in this paper's scope.

4.2.2 Modeling Heuristics, Strategies, and Prior Knowledge. The wayfinding behavior is motivated by a desire to reach the destination using the information in the head (i.e., belief, strategies, prior knowledge) and information in the world (i.e., directional information from visual cues). In the scope of this research, we model the three strategies mentioned in Section 4.2.1.

We model the three heuristics in a sequential order starting from floor level strategy. From the location cognitive agent is spawned (i.e., the origin of a wayfinding task), the agent employs its visual perception model (see Section 4.1.1) to check if the communicated destination is on the same floor level or not. Equation 1 formulates the vertical distance between the origin and destination floor level. The first letter of the detected directional signage and room numbers on the wall is compared with the first letter of the destination room number provided. Consequently, the agent transit to one of the two states: "Find an Escalator/Lift/Stairs to move up or down the floor" if it does not match or "Explore on the same floor" if the destination is inferred to be on the same floor level.

$$\Delta_V(S_{o_i}, S_d) = \text{'}I\&\text{'} \begin{cases} \tilde{D} & [S_{o_i} - S_d] \neq 0 \\ \emptyset & [S_{o_i} - S_d] = 0 \end{cases} \Big| \; i = (1, 2, ..n) \qquad (1)$$

Functions Δ_V (Vertical distance) output the state-decisions made by Floor strategy S1. S_{oi} is a list of sign and room number observed while agent's exploration. n is the number of sign observed. S_d is the destination sign assigned to agent at the beginning of the simulation. The agent is assigned a new temporary sub-goal of $\tilde{D}$ (e.g., lift, stairs or escalator) in the case of floor level change and ∅ in the case of same floor level.

Strategy S2 is initiated after the completion of S1. It formulates the horizontal distance between the origin and destination location. Equation 2 formulates the horizontal distance calculation.

$$\Delta_H(S_{o_i}, S_d) = \textbf{arg min} \left| S_{o_i} - S_d \right| \Big| \; i = (1, 2, ..n) \qquad (2)$$

Functions Δ_H (Horizontal distance) output the directional-decision made by S2. A simple subtraction operation is performed between the currently observed and destination signage room number. The agent turns towards the directional that minimizes the perceived distance between the currently observed agent's location with the expected destination location. For example, destination room number (S_d: 232) will be close to room numbers ($o1$: 230-234) and further from room number $o2$: 220). Thus, choosing the direction that leads to rooms 230-234 instead of room 220 will intuitively minimize the distance to the destination.

Strategy S3 is initiated after S1 and S2 and at a decision-point when the agent is confronted with a route-choice decision and none of the routes are more probable than the others. Please refer to Section 4.3 for more detail.

4.3 Wayfinding Uncertainty Model

An occupant's uncertainty for a wayfinding task (e.g., navigating to 'Cafe') in an unfamiliar environment varies over time. It depends on multiple factors such as wayfinding information sources in an environment, the spatial layout, the occupant's spatial ability, and the consequence of failure. We propose a computational model of overall wayfinding uncertainty by modeling the two most common and prevalent uncertainty during wayfinding [Jonietz and Kiefer 2017].

- Route-choice uncertainty (U_r): This uncertainty originates when an occupant is at a decision point and has to select a route out of the multiple route choices.
- Affirm route uncertainty (U_a): This uncertainty originates when an occupant is in-between decision points (e.g., a long corridor, large open space) and tries to ascertain if its current location is on the correct route towards the destination.

4.3.1 Affirm On-Route Uncertainty. To incorporate the above-mentioned uncertainty, we propose a continuous computation of uncertainty U_a as a function of the time elapsed between the last perceived information and the current time. It is based on the hypothesis that uncertainty increases directly proportional to the time elapsed between information gain.

$$U_a = (t_c - t_c) \times \theta \tag{3}$$

U_a is a function of three attributes: simulation time of last perceived directional information (t_s), current simulation time (t_c) and the uncertainty constant θ. θ is parameterized on the finding of human study (Section ??).

4.3.2 Route Choice Uncertainty. U_r is zero when the agent's current location is outside the proximity of any decision point. This is because the agent is outside the decision-making zone and has not been tasked to analyze the wayfinding challenge to select an appropriate response. U_r is ∇ when it is inside the region of influence of a decision-point.

$$U_r = \begin{cases} 0 \text{ if } |l_{dp_i} - l_a| > \gamma \\ \nabla \text{ if } |l_{dp_i} - l_a| \leq \gamma \end{cases} \quad dp_i \in \{1, \dots, |\mathrm{DP}|\} \tag{4}$$

l_{dp_i} and l_a are the 2D location information for the ith decision point and agent's current location. γ is the user-specified radius to describe the decision-point's circular region of influence.

$$\nabla = -\sum_{i=1}^{n+1} p(x_i) \log_2 p(x_i) \,\Big|\, x_i \in X \tag{5}$$

∇ simply represents Shannon's formula for information entropy. Uncertainty is cause due to two attributes: the number of possible outcomes and the probability distribution of belief in electing each outcome. For example, uncertainty increases as the number of possible outcomes increases (i.e., increase in the wayfinding action list: e.g., x1, x2, x3,.., xn) and the probability of any particular outcome, $p(x_i)$, decreases. Uncertainty is low when one outcome stands out with a high probability of selection compared to all others. X is the set of all wayfinding actions that can be taken at a decision-point. It comprises of $n-1$ route-choices at any given intersection, back-tracking to previous decision-point (i.e., the corridor of approach), and pause behavior to simulate looking around and seeking more information.

$p(x_i)$ is computed by employing a multi-source information fusion method as proposed in Section 4.4. A hypothetical decision confidence distribution grounded in spatial cognition literature is then employed to compute each information source's confidence probability for perceiving the directional information for each possible outcome $x_i \in X$ (Table 1). Information perceived from signs carries the highest weightage, followed by short-term memory. The crowd and space

Information Sources	Confidence Probability
Sign	0.5
Memory	0.3
Crowd	0.1
Space	0.1

Table 1. Four hypothetical probability distributions (Sign, memory, space, crowd) are employed to compute the confidence probability in choosing an outcome.

have identical confidence since their interaction, and which one impacts more has not been investigated thoroughly. Table 1 is user-defined parameters and can be adapted during simulation. At the end, the framework outputs a routechoice with the highest confidence. The advantage of using this framework is that it can be extended by including additional information sources such as floor plan layout, wall texture, landmarks, ambient lighting, etc.

4.4 Cognitive Agent Decision Making model

Wayfinding is the process of constantly picking up information from the environment and forming a decision when at a decision point. To formulate this process, we propose an information-theoretical based decision making framework. The proposed cognitive agent employs its perception model to quantify the information from N wayfinding information sources (e.g., signage, spatial layout, crowd flow, memory, etc.) to guide its macro-decisions at an intersection.

$$
\begin{aligned}
\mathbf{o}_t &= O_t(l),\ \Gamma = \Gamma(l) \\
f_i(\mathbf{o}_t) &= P_i(X \mid \mathbf{o}_t) \Big| i = 1, \cdots, N \\
\mathbf{F} &= \left[f_1(\mathbf{o}_t), \cdots, f_N(\mathbf{o}_t) \right] \\
G(\mathbf{F}) &= P(\hat{X} \mid \mathbf{F}) \Big| \hat{X} \in 2^X
\end{aligned}
$$

X is the set of all M macro-decisions. Macro-decisions is a list of route-choices that an agent can take at a decision point (e.g., all the routes (edges) going out from the concerned decision point (nodes)). Vector o_t consists of the observations made of the N information sources at time t from location l (note: location l should be within the decision-zone (see Equation 4)). Γ is the set of neighboring positions for location l. The functions f_i are constituent macro-decision-making models based on N physical information sources. For example, to model the macro-decision model f_{sign} (i.e., agentsignage interaction), we can leverage state-of-the-art methods, such as [Dubey et al. 2021]. Similarly, we can model f_{space} (i.e., influence of space on route-choice), f_{crowd} (i.e., influence of crowd on route-choice), and f_{memory} (i.e., influence of past familiarty of the environment on route-choice) by leveraging the specific current best computation model. Matrix $F_{M \times N}$ consists of the constituent models' probability distributions as shown below.

$$
\mathbf{F}_{M\times N} = \begin{array}{cc} & \begin{array}{cccc} N_1 & N_2 & \dots & N_{|N|} \end{array} \\ & \begin{pmatrix} f_{11} & f_{12} & \dots & f_{1|N|} \\ f_{21} & f_{22} & \dots & f_{2|N|} \\ \vdots & \vdots & \vdots & \vdots \\ f_{|M|1} & f_{|M|2} & \dots & f'_{|M||N|} \end{pmatrix} \begin{array}{c} M_1 \\ M_2 \\ \\ M_{|M|} \end{array} \end{array}
$$

Function G fuses F into a single probability distribution over 2^X, the powerset of X.

Based on [Dubey et al. 2019a; Xiao 2019], a multi-source information fusion method is proposed that considers JensenShannon divergence (JSD) and Shannon entropy (H) in order to determine the confidence in each of the macro-decisions. JSD is employed to measure uncertainty between information sources and entropy is used to measure uncertainty within information sources. The framework described in this section also takes as input N probability distributions in the form of F and outputs either one of M macro-decisions or no decision.

The steps involved in this information-theoretical approach are described below.

Step 1: We compute the JSD between each pair of sources.

$$
\begin{aligned} JSD_{i,j} = & \quad \tfrac{1}{2} \textstyle\sum_x^X \mathbf{F}_i(x) \cdot log_2(A) \\ + & \quad \tfrac{1}{2} \textstyle\sum_x^X \mathbf{F}_j(x) \cdot log_2(B) \end{aligned} \tag{6}
$$

where $A = \frac{2\cdot\mathbf{F}_i(x)}{\mathbf{F}_i(x)+\mathbf{F}_j(x)}$ and $B = \frac{2\cdot\mathbf{F}_j(x)}{\mathbf{F}_i(x)+\mathbf{F}_j(x)}$.

Step 2: The average JSD (JSD_i) of information source i can be calculated by Equation 7.

$$
JSD_i^{\mu} = \frac{\sum_{j=1, j\neq i}^{N} JSD_{i,j}}{N-1} \tag{7}
$$

Step 3: The support degree Sup_i of information source i is defined as follows:

$\mathrm{Sup}_i = \frac{1}{max(\epsilon, JSD_i^{\mu})} \Big| \, 0 < \epsilon \ll 1$(8)where, in practice, $\epsilon = 10^{-5}$ is used.

Step 4: The credibility degree Crd_i of information source i is defined as follows:

where the range of Crd_i is [0, 1].

$$Crd_i = \frac{Sup_i}{\sum_{j=1}^{N} Sup_j} \cdot \left(1 - \frac{1}{N} \sum_{j=1}^{N} JSD_j^{\mu}\right) \tag{9}$$

where the range of Crd_i is $[0, 1]$.

Step 5: In this step, we measure the normalized Shannon entropy of each information source i, which is the entropy of source i divided by the maximum possible entropy for X.

$$\tilde{H}_i = -\sum_{x}^{X} \mathrm{F}_i(x) \cdot log_2 \, \mathrm{F}_i(x) \; / \; log_2 \frac{1}{M} \tag{10}$$

Step 6:

Based on the normalized entropy $\tilde{H}_i$, the credibility degree Crd_i is adjusted, giving the confidence in the information provided by source i. On account of the confidence in each information source i, the confidence distribution over X will be obtained as follows:

$$G = \sum_{i=1}^{N} Crd_i \cdot (1 - \tilde{H}_i) \cdot \mathrm{F}_i \tag{11}$$

Steps 1 through 6 correspond to G(F), which transforms the input F into the output confidence distribution over X, which is a subset of 2^X. The rule that this framework uses to output a macro-decision is based on the highest confidence in the output distribution.

$$G(\mathbf{F}) = \begin{cases} arg \max_{x \in X} \left(G(\mathbf{F})\right) & \nabla \leq \theta_U \\ back - tracking & \nabla > \theta_U \end{cases} \tag{12}$$

If this value exceeds uncertainty threshold θ_U (i.e., parameterize from participant data collected in Section ZZ), the agent is highly uncertain and back-tracking behavior occurs. If the value is within θ_U, the agent is sufficiently confident in the corresponding macro-decision, to make a decision.

4.5 Cognitive Agent Wayfinding Model

Figure 2 presents the overall working and architecture of the proposed agent decision-making model under uncertainty. We model agent's behavior as a finite state machine (FSM) where an agent can be in exactly one of a finite number of states at any given time. The FSM can change from one state to another in response to some input. The proposed model has five states in which an agent can be:

- *Explore*: In this state, agent explores the environment seeking for directional cues.
- *Sub-goal*: In this state, agent is assigned a new temporary sub-goal of (Staircase/Escalator/Lift) in order to perform a shift in floor level.

- *Lost*: In this state, the agent showcase lost behavior (i.e., pause and look around, u-turn back to previous decision-point) when the wayfinding uncertainty is high and above the parameterized threshold (σ).
- *Decision-Node*:In this state, agent is inside the decision-zone and elect most-certain route at an intersection.
- *Execute*: In this state, agent navigates to the identified destination/sub-goal/selected route.

In Section ??, we have presented the correlation between participant's wayfinding behavior and the perceived continuous uncertainty (see Table ??). Exceeding the uncertainty value of σ, most participants showed lost behavior by either pausing for a while to look around and seek additional visual cues or returning to the previous decision point. Agent's *Explore* state is changed to *Lost* state when the simulated uncertainty increases above the established threshold of σ. Agent's *Explore* state is changed to *Sub-goal* state when the agent perceives that the destination is on a different floor level when prompted by directional cues as per Floor strategy (Section 4.2.1. *Sub-goal* state changes back to the *Explore* state when the agent is on the desired floor level. The agent in *Explore* state or *Lost* state transit to *Decision-Node* state when its within the decision-node influence. The agent transit to *Explore* state from *Decision-Node* state after electing a route and exiting the decision-node zone of influence. The agent transit to *Execute* state from all

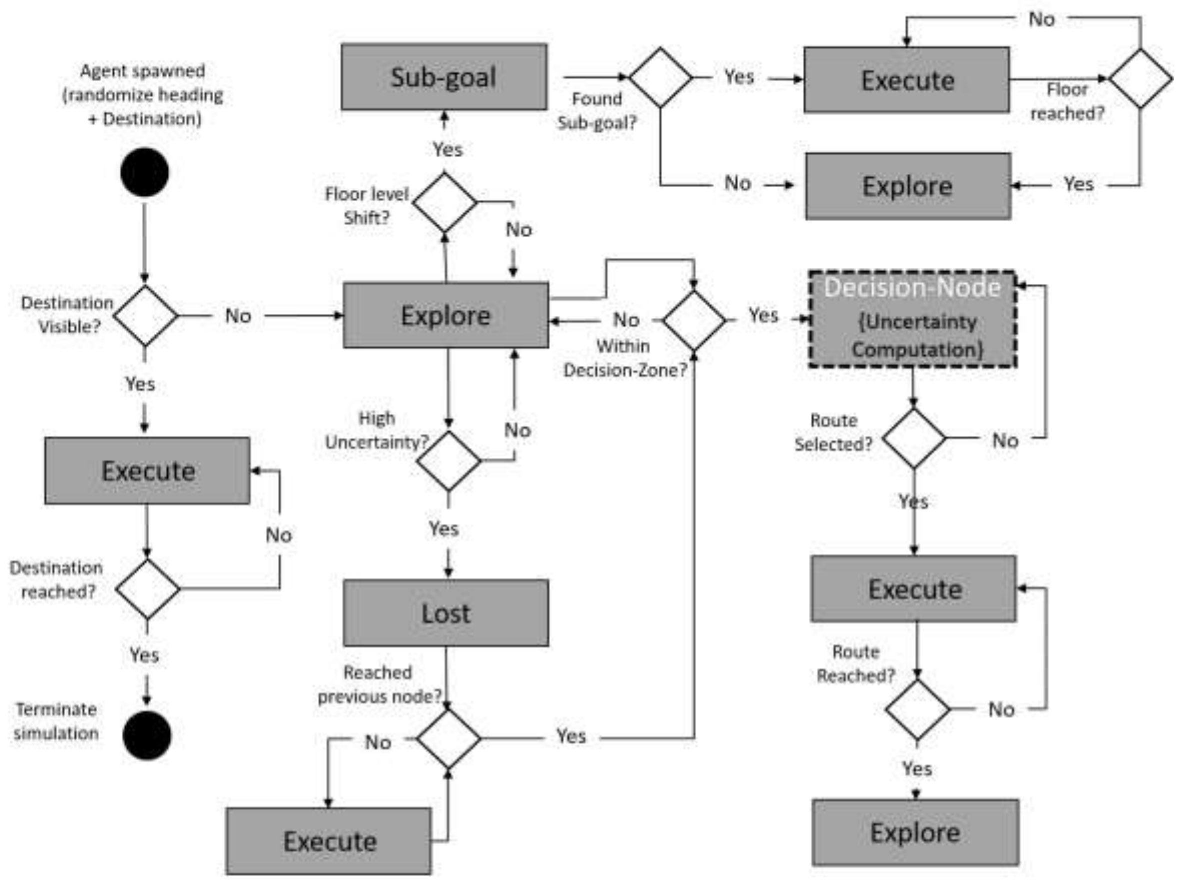

Fig. 2. Overview: A state machine diagram depicting agents' wayfinding model under uncertainty.

other states if it has been assigned one of the following three goals: (1) Final destination (2) Sub-goal (3) Selected route at a decision-node.

5 SIMULATION RESULTS & VALIDATION

In this section, we describe simulation results. We performed three similar wayfinding tasks with 11 participants and agents to validate the proposed cognitive agent. A realistic and accurate model of an educational building was developed with an exact replica of its signage system. Continous uncertainty measure was recorded for both the participants and humans. We visualize the average uncertainty value per location (i.e., discretize as grids) as shown in Figure 3. We noticed higher uncertainty value at most decision points, areas that lacked signage, and long corridors in both participants and simulated agents. Preliminary analysis of route-choice behavior at decision points also showed similar probabilities of selecting routes. We will perform further validation using the measure as suggested in 5.1.

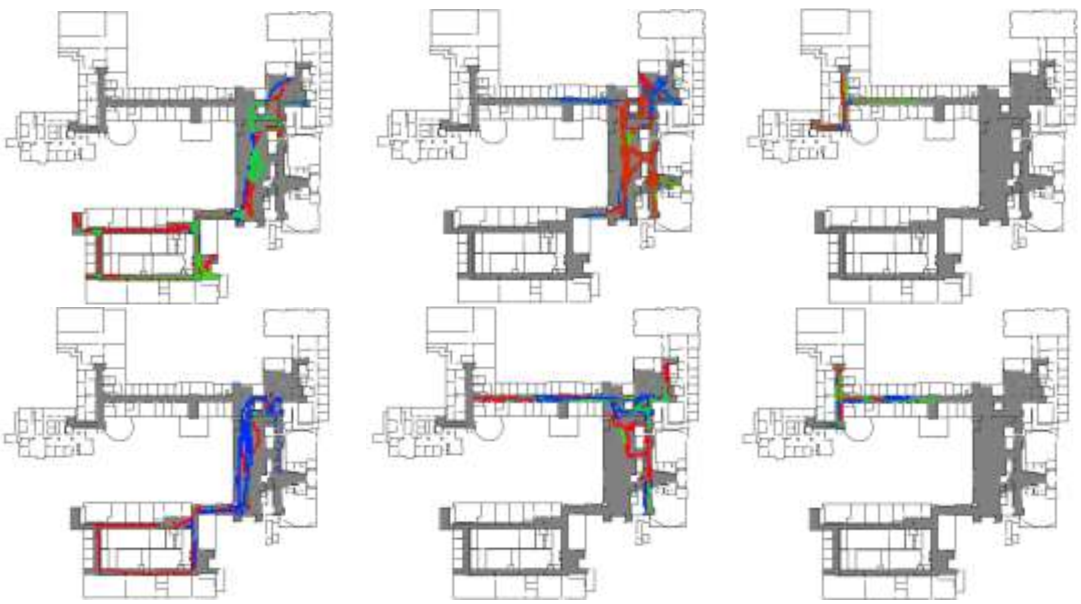

Fig. 3. Comparison of participants uncertainty (bottom column) with agent uncertainty map (Top column) for three wayfinding tasks.

5.1 Validation

To validate and test the proposed evidence-based cognitive agent model, we compare it against human data and shortest-path agents (e.g., A* or Dijkstra's) that follow shortest path heuristics. We collected data using two different signage system scenarios for the same building (see Section xx). Out of XX participants, YY participants' data was recorded with the signage system 1, and ZZ participants' data was recorded with the signage system 2. Participants' data from signage system 1 is used for training, and participant data from signage system 2 is used for validation of the proposed cognitive agent model.

The analysis of simulation results aims to quantify the observed similarity in wayfinding behavior between the proposed evidence-based cognitive agent and human participants. For evaluation we employ the following measures:

- Wayfinding Behavior Similarity Index (WBS-Index): A novel WBS-Index is proposed to perform a microscopic evaluation of the wayfinding behavior. We assign a cumulative score to a wayfinding behavior by measuring the occurrence of backtracking, hesitation (i.e., reduction in walking speed), stop, and informationseeking behavior during a wayfinding task. For example, a score of 6 is assigned to a trajectory produced by an individual who stopped twice, backtracked and hesitated once, and sought wayfinding information twice. A score of 0 is assigned to a shortest-path agent that has 100% knowledge of the environment (i.e., this agent produces zero counts for each backtracking, hesitation, stop, and information-seeking behavior).
- Uncertainty Similarity Index (US-Index): An uncertainty similarity index compares the difference in the cognitive agent's uncertainty for a wayfinding task with the continuous measure of perceived uncertainty recorded by participants for the same wayfinding task.
- Path-Edit Distance: measures the difference between two paths by counting the minimum number of operations required to transform one path into the other [Dubey et al. 2022]. For each wayfinding task (origin-destination pair), we record the route choice at each decision point as a string (e.g., "LFRL" for a path that traverses four decision points and elects one of the following routes. L: left, R: Right, F: Forward). Both human and agent trajectories will produce two such strings for a wayfinding task. We employ Levenshtein distance to compute the minimum number of edits required to transform one string to another.
- Average Path Distance: measures the average path distance per wayfinding task for all trajectories [Dubey et al. 2022; Huang et al. 2017; Madl et al. 2015].

6 DISCUSSION & CONCLUSIONS

In this study, we developed a cognitive wayfinding agent that integrates psychological uncertainty into the simulation. The agent could make sign-inference and showcase back-tracking behavior based on the uncertainty threshold from the empirical data. We compared the agent performance with eleven human participants. We found that integrating back-tracking behaviors into the process significantly decreased the agents' wayfinding performance compared to the baseline agent, making the simulation more human-like. Moreover, route-choice uncertainty matched with real participants to some degree, and removing uncertainty stimulation significantly decreased the similarity between the agent and the real participants. It indicates that navigation uncertainty can be an important factor to consider when simulating realistic wayfinding behaviors. However, route choice and traveled time couldn't explain all real participants' uncertainty. More latent variables such as participants' priors and short-term memories that contributed to uncertainty should be considered.

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