Automation in Construction 135 (2022) 104131

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Beyond the shortest-path: Towards cognitive occupancy modeling in BIM

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ARTICLE INFO

Keywords:
Agent-based modeling
Cognitive agents
Wayfinding
Indoor navigation
BIM
Building performance simulations

ABSTRACT

Current approaches to simulate occupants' wayfinding in AEC mostly employ direct routing algorithms that assume global knowledge of the navigation environment to compute a shortest path between two locations. This simplification overlooks evidence concerning the role of perception and cognition during wayfinding in complex buildings, leading to potentially erroneous predictions that may hinder architects' ability to design wayfinding by architecture. To bridge this gap, we present a novel simulation paradigm entitled Cognitive Occupancy Modeling in BIM to simulate wayfinding by means of a vision-based cognitive agent and a semantically-enriched navigation space extracted from BIM (Building Information Modeling). To evaluate the predictive power of the proposed paradigm against human behavior, we conducted a wayfinding experiment in Virtual Reality (VR) with 149 participants, followed by a series of simulation experiments with cognitive and direct routing agents. Results highlight a significant correspondence between human participants' and cognitive agents' wayfinding behavior that was not observed with direct routing agents, demonstrating the potential of cognitive modeling to inform building performance simulations in AEC.

1. Introduction

Previous research shows that people often get lost or disoriented during wayfinding in unfamiliar buildings with complex multilevel geometries or mixed-used development such as transit hubs, hospitals, shopping malls[1–9] and museums [100]. The implications of feeling lost are numerous and range from confusion, stress and frustration [9–11] to unnecessary operational costs and delays [12]. Despite these negative implications and although considerable evidence shows that wayfinding is largely shaped by preliminary design decisions [1,35,38,100,101] (e.g., the location of the entrance and circulation cores or visibility between spaces and floors), wayfinding in architecture is primarily associated with signage design [13]. As a result, wayfinding aspects are usually addressed at the very end of the construction process and are mostly delegated to environmental communication designers. The latter frequently face the complex and at times impossible task of making a building legible [14,15] regardless of its architectural configuration or functional organization that are often determined early on [8,9,13,16–18]. This disconnect between wayfinding and architectural design overlooks the potential of architectural configuration to directly shape occupants' wayfinding experience and nudge their behavior to achieve local and global objectives. Bridging this gap is instrumental to align the intended wayfinding experience with the actual one to ultimately achieve various performance objectives that are related to occupants' wayfinding behavior in buildings, including efficiency, productivity, sustainability, health, and wellbeing.

A powerful approach to increase the integration of wayfinding evaluation into the architectural design process, and to harness the potential of architecture to shape occupants' wayfinding is the use of computational, agent-based simulations [35,38]. This approach is particularly relevant today given the ubiquity of Building Information Modeling (BIM), resulting in digital representations of buildings throughout their life cycle. Nevertheless, a common tendency in pedestrian modeling and occupancy models in AEC is to simplify the complex process of wayfinding to a routing problem, formulated as the 'Shortest-Path' problem [19–23]. To calculate an optimal path, the environment is abstracted into nodes and edges and the shortest path between two points is classically computed using direct routing

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https://doi.org/10.1016/j.autcon.2022.104131
Received 20 May 2021; Received in revised form 20 November 2021; Accepted 3 January 2022
Available online 24 January 2022

algorithms such as Dijkstra's algorithm and A* [24,25]. However, unlike in computer science where the computation of an optimal path relies on having a complete representation of the environment, human wayfinding in unfamiliar buildings involves a gradual discovery of the space from an ego-centric perspective, one step at a time [26–28]. This process forces one to navigate on the basis of partial information, and subsequently become prone to erroneous decisions [8,28–30]. Consequently, occupants who perform wayfinding in unfamiliar buildings often present substantial deviations from the shortest or fastest route [8,17,31]. This discrepancy raises fundamental questions concerning the applicability of direct routing algorithms to reliably forecast occupants' wayfinding in complex buildings.

To advance occupancy simulations in AEC beyond these simplified models, a profound understanding of wayfinding is required. Cognitive science provides theoretical and empirical foundations to model wayfinding with an appropriate degree of detail. In cognitive science literature, wayfinding and locomotion are regarded as two principal components that underpin human navigation [26,27]. While locomotion refers to the motor aspects of navigation, wayfinding involves spatial decision making and movement towards unfamiliar destinations located outside of one's immediate perception range [26]. In this sense, the role of external information encoded in the spatial configuration and functional organization of buildings is cardinal to support wayfinding decisions [3,13,17,18,32,33]. In complex multilevel buildings, floors and walls often occlude sight-lines, revealing only partial information. Such limited visibility in the horizontal and vertical dimensions is associated with specific wayfinding strategies and reliance on background expectations to support wayfinding under uncertainty [11,31,33–35].

Cognitive modeling, in contrast to direct routing, seeks to simulate wayfinding through modeling cognitive processing mechanisms that are grounded in the above-mentioned evidence and in theories from cognitive science. The result of this modeling process is a cognitive or intelligent agent that is able to perceive the external environment through sensors (e.g., visual perception, auditory perception), has an internal representation of the environment, learning capacities, commonsense knowledge to reason upon the perceived sensory input, strategies to achieve goals or maximize some objective, and mechanisms of motor movement to act in the environment. The representation of the environment and the information it encodes are the basis for agents' perception and decision making. Cognitive agents in the context of wayfinding were originally developed to test existing or novel hypotheses in cognitive science, followed by the validation of different agent models against human behavior. Nonetheless, applications of cognitive modeling to simulate wayfinding have been widely applied in the field of computer graphics and in robotics. In computer graphics, cognitive models were mostly applied to simulate realistic movement of virtual agents for the entertainment industry. In the field of robotics, cognitive modeling inspired major advancements in robotic navigation that diverge from classical direct routing. Specifically, it led to a shift from 'Map-Based' robots that apply direct routing to 'Mapless', vision-based robots [36,37] that implement cognitive modeling to navigate in unfamiliar real-world environments on the basis of perceived and stored visual information. In AEC, cognitive modeling has so far not been directly applied to simulate wayfinding. Moreover, the potential of BIM to generate an information rich environment and support agents' wayfinding on the basis of local perception has been largely overlooked.

To bridge this disconnect between wayfinding and architecture, the work presented in this paper combines evidence and theory from cognitive science together with the aforementioned advances in cognitive modeling, vision-based robotics, and BIM. This holistic combination underpins our proposed modeling paradigm entitled Cognitive Occupancy Modeling in BIM. In contrast to direct routing agents, the proposed paradigm outlines the necessary cognitive processing mechanisms (e.g.,vision, wayfinding strategies and cognitive maps) and environmental information (e.g., metric, semantic, volumetric, topological and connectivity information) required to simulate wayfinding in a cognitively plausible manner.

To test the feasibility of this paradigm, we employ cogARCH, a software implementation developed in [38]. This previous work presented an initial version of the simulation software employed in the current paper. In addition to the software development, the study conducted by Gath-Morad et al. included a preliminary sensitivity analysis showing that cognitive agents were able to capture and reflect the differences in visibility of the environment, while shortest-path agents, as expected, did not. cogARCH provides a vision-based cognitive agent complemented by a BIM-generated, hierarchical and semantically enriched navigation space used to support agents' perception and cognitive decision making. In this work we move beyond this sensitivity analysis to quantify the wayfinding performance of a cognitive agent model and a shortest-path agent model against wayfinding by human participants observed in a VR experiment. This required redesigning agents' background expectations and designing simulation experiments that are comparable with the wayfinding experiment conducted in VR.

To critically assess the proposed paradigm against classical direct routing, we conducted two interrelated studies. The first simulation study compares the variability in wayfinding behavior observed by vision-based cognitive agents and direct routing agents under three building conditions with systematic variations applied to their volumetric design. These variations manipulate the degree of visibility between floors through systematic architectural design actions (e.g., introducing atria between floors or varying the transparency of building surfaces). To assess which agent model (cognitive agents' versus direct routing agents) better corresponds with human wayfinding, we conducted a second study in which we perform a wayfinding experiment in VR with 149 participants. Results from a total of 890 wayfinding tasks sampled in the VR experiment are compared against shortest-path and cognitive agents. The correspondence between simulated behavior and observed one are then analyzed statistically and spatially, showcasing strong evidence concerning the limitations of direct routing and the potentials of cognitive modeling to capture the effects of architecture on wayfinding.

The contributions of this paper are three-fold: (1) it highlights concrete limitations of direct routing agents (that are often employed to simulate movement in building performance simulations) to forecast wayfinding in multilevel buildings. This is done by providing a dual perspective of wayfinding in cognitive science versus routing in computer science. (2) It provides empirical results that confirm these limitations. This is demonstrated by the invariant wayfinding behavior of shortest-path agents which fails to capture the effect of architectural variations between conditions. This contrasts significantly with observed human wayfinding behavior under the same conditions in which the same variations had a significant effect on human wayfinding. (3) It showcases how a vision-based cognitive agent is able to overcome these limitations, presenting significant variability in wayfinding behavior in response to the same architectural design variations. This is highlighted by evaluating and contrasting shortest-path versus cognitive agents' forecasting quality of human wayfinding through several metrics (accuracy, precision, recall, f1-score, ROC-AUC), revealing that the proposed cognitive agent consistently outperforms the forecasting quality of the shortest-path agent with regards to the predicted changes in wayfinding behavior under different building configurations.

2. Background and related work

2.1. Direct routing in AEC simulations

The majority of agent-based models that simulate navigation in AEC adopt a classical three-layer architecture which originates in the field of pedestrian modeling [39,40]. These layers model agents' strategic, tactical, and operational behavior [41]. At the strategic layer, agents choose between possible destinations to form an activity schedule [40].

At the tactical layer, agents plan a route from an origin to a destination. At the operational layer, agents' locomotion behavior such as obstacle avoidance, speed, and acceleration is calculated (which is often simulated using the social force model [42] or Optimal Reciprocal Collision Avoidance [43]).

Wayfinding is addressed at the tactical layer in the classical three-layer architecture, where it is formulated as a routing problem and solved using shortest-path algorithms [44] or its variants [28,40,45]. Variants of shortest-path algorithms are prevalent in egress evacuation simulations [46,47] where the assumption is that agents follow the shortest path that is also the fastest and safest evacuation route [48]. To calculate these 'optimal' paths, the shortest path is weighted with additional heuristics in addition to distance. These heuristics include the least angle heuristic, longest-leg first heuristic, shortest-leg first heuristic, fewest turns heuristic, less-congested-leg heuristic, and widest-leg heuristic [28,45,49,50]. Applying the shortest-path heuristic or its variants to perform routing calculations may capture some route choice preferences. Yet, direct routing still fails to represent movement behavior that is the result of a wayfinding process involving perception and cognition, or the interplay between them.

With regard to perception, despite the well known importance of visual information to support wayfinding decisions [8,15,33,51,52], the representation of the environment required for routing calculations is a complete graph that represents the walkable space (e.g., a grid representation) or the connectivity between spaces (e.g., a network graph). Attempts to encode visibility information in such graphs have been made [28,49]. Yet, although this type of graph representation is very useful for routing calculations, it is not possible to encode in it the full complexity of volumetric visual perception from an egocentric perspective given a complex multilevel building. In such buildings, it is necessary to account for visibility through voids or transparent surfaces that emerges from the complex interaction between the architectural configuration and agents' 3D field of view, heading, head movement, and height. Empirical evidence shows that information captured in humans' field of view during wayfinding in the vertical has a significant impact on wayfinding and plays an important role in mitigating the risk of getting lost [35].

Regarding cognition, direct routing overlooks inherent cognitive limitations and mechanisms involved in wayfinding. Most importantly, it assumes that occupants have a precise representation of the environment and are completely familiar with it, which is often not the case, especially in public or large-scale buildings with a high degree of complexity and choice. Nonetheless, this assumption is necessary to perform routing calculations that rely on having a pre-generated and complete representation of the environment from which the shortest path can be computed. This assumption stands in sharp contrast to evidence and theory from cognitive science which shows that wayfinding is bounded by humans' sensory-motor perception range and often involves movement in an unfamiliar environment towards a novel destination that is not visible [26].

To cope with this uncertainty people apply different search strategies [8] as well as background expectations [53] to approximate the location of their destination and find a path towards it. These strategies involve an exhaustive search such as in the perimeter strategy (i.e., moving along the perimeter of an environment to reduce the probability of visiting the same space [54]), the lawnmower strategy (i.e., moving in a sequence of straight parallel lanes [55]), and the directed random search strategy (i.e., choosing a turn that has the lowest likelihood of backtracking [27]). In multilevel buildings where visual access is limited and there are inherently more movement options, additional wayfinding strategies have been observed [8]. These include the central point strategy (i.e., adhering to public and visually integrated areas at the expense of performing detours), the direction strategy (i.e. first minimizing the horizontal distance to the approximated target location, irrespective of level changes) and the floor strategy (first minimizing the vertical distance to the target, irrespective of its horizontal location). Whereas the aforementioned strategies often result in considerably longer paths at the expense of minimizing the risk of getting lost, direct routing delegates the decision making process to routing algorithms that calculate the fastest or shortest path (e.g., Dijkstra's or A*).

Although through different processes, wayfinding and routing produce the same output, a path between an origin and a destination. Whereas in routing a complete graph is a prerequisite to calculate a path, in wayfinding, the graph is generated on-the-fly through visual perception, knowledge-based reasoning and wayfinding strategies. In this sense, while routing is concerned with the efficient computation of the shortest or fastest route irrespective of occupants' bounded knowledge, wayfinding attempts to model how a bounded agent would acquire, process and act upon the knowledge perceived from the environment to find their destination and plan a path towards it. In building performance simulations that consider occupants' behavior in buildings, this important distinction between routing and wayfinding is often overlooked and de-emphasized, reflected in the fact that direct routing dominates occupancy simulations in AEC [23,56,57].

2.2. *Cognitive modeling of wayfinding*

As shown in the previous section, direct routing algorithms simulate wayfinding by computing the shortest path given a complete graph of the environment. In contrast, cognitive modeling seeks to model the process of wayfinding by modeling the interplay between cognitive processing mechanisms (i.e., knowledge in the head, [16]) and information in the environment (i.e., knowledge in the world, [16]). In the context of agent-based modeling in social science and cognitive robotics these models are referred to as 'cognitive agents' [58,59], whereas in computer graphics and artificial intelligence they are often referred to as 'intelligent agents' [30,60]. In social science, the motivation for developing cognitive agents is to formalize theories and test existing and novel hypotheses [30], which usually involves comparing agents' behavior against human observations [61]. In robotics, cognitive models are implemented in cognitive robots to support wayfinding in real-world environments, facing the need to simulate wayfinding in an accurate manner given a dynamic and complex environment [62]. In artificial intelligence and computer graphics, intelligent agents are developed to populate virtual worlds, placing an emphasis on simulating realistic navigation. Such models highlight the trad-off between realism and efficient performance [63,64].

Our work is mostly grounded in social science and the robotics approach to modeling cognitive agents, yet it is inspired by the methods employed by the artificial intelligence community to develop intelligent agents. Accordingly, we consider agents as entities able to perceive the external environment through sensors (e.g., visual perception, auditory perception). These agents may have an internal representation of the environment, learning capacities, commonsense knowledge to reason upon perceived sensory input, global and local wayfinding strategies to search for a destination or maximize some objective, and motor capacities to act upon their decisions in the environment [30,58,60,61].

Authors in [61] provide a comprehensive review of methods applied in cognitive modeling to simulate wayfinding. Broadly speaking, methods to model agents' cognitive decision making and commonsense knowledge vary and range from 'symbolic models' that emphasize explicit rules to model behavior [65], 'neural network models' where agents learn rules from training data instead of encoding explicit rules [30,66,67], and general cognitive architecture models (e.g., ACT-R or SOAR) that employ a combination of the other two methods [59]. Similarly, methods to model the navigation environment to accommodate cognitive-based decision making are highly diverse and are often crafted to correspond with the cognitive model. The environment can be represented as a semantic network graph that connects decision points [59,68], a grid graph that represents the walkable space [69], or a room/region graph that models the connectivity between spaces [38,40]. Spatial memory and learning are modeled using an internal graph representation of the environment that is based on the agents' ego-centric or allocentric perception [28,68,70–72]. Most agents have short-term and long-term memory in which this representation is stored, forgotten, and distorted using distance decay and directional distortion of visited and perceived locations [72]. Sensory perception mostly emphasizes visual perception which can be modeled using visibility graphs, isovist or space syntax analysis [69], ray-casting to simulate agents field of view in 2D [40,52,69] or in 3D [35,38,70] as well as scene processing methods that include scene classification, semantic segmentation, object detection, pose estimation, physics-based reasoning, saliency prediction, affordance prediction, and 3D reconstruction [73].

Earlier studies that model wayfinding by means of cognitive agents mostly focused on simulating wayfinding through the generation of a 'cognitive map' [74]. The cognitive map hypothesis [75] postulates that neural encoding of place, grid and direction cells in the brain form an internal representation of previously navigated environments to inform memory-based wayfinding [76]. Several computational models of cognitive agents that focused on simulating wayfinding using such an internal representation have been proposed [67,68,71,72]. The validation efforts of these models against human behavior are limited [61]. NAVIGATOR [68] proposed a model of wayfinding using a semantic network representation in which agents can perceive information locally and store the input in memory to calculate novel paths step-wise. The model qualitatively replicated human wayfinding errors. Agents and humans performed errors at locations with more information, or at locations where complex navigational actions were required. Moreover, there was a correspondence in errors due to misidentification of the goal. Additional approaches to model cognitive aspects during wayfinding proposed to integrate visibility information to inform decision making [40,77]. For instance, Penn and Turner [77] developed an 'exosomatic visual architecture' to simulate agents' undirected wayfinding (i.e., exploration). In their implementation, the environment was represented as a grid graph and each cell was encoded with pre-computed visibility information derived from a space syntax analysis. Agents' visibility was bounded by a two-dimensional field of view and their decision making was informed by this visibility input, used to move towards the most visually integrated cell. This model was validated against real shoppers behavior in a department store. Results indicate a positive correspondence between real shoppers and agents flow. Another approach to model visibility is presented by [43] who provide a hierarchical representation of a 3D environment through 2D layers to represent the environmental details perceived by agents', used to inform agents' local decision making. Their validation was limited to the collision avoidance and pedestrian flow based on 'fundamental diagrams'. The main shortcoming of these models is that they focus on either visibility or memory (i.e. cognitive map), instead of modeling the interplay between them [16].

In cognitive robotics, the challenges of wayfinding in real-world environments have led to a more integrative approach that combines an internal representation with 3D visual perception to support 'Mapless' robot navigation. Whereas 'Map-Based' is almost analogous to routing, 'Mapless' applications are much closer to wayfinding, [62,78]. 'Mapless' applications employ methods to acquire and store visual clues from the environment to map the navigation space in real time and support robots' wayfinding in an unfamiliar environment. Methods to support robots' visual perception include image segmentation, optical flow, or the tracking of features across frames. Across these applications, there is no global representation of the environment. Rather, it is perceived and generated on-the-fly as robots move from one location to another.

Only recently efforts have been made to apply this integrated approach to simulate wayfinding by virtual agents in virtual indoor environments. The majority of these studies apply it to simulate aided-wayfinding by externalized symbolic information, such as signage and maps [79–81]. Far fewer studies focus on applying vision-based cognitive agents to simulate wayfinding by architecture in buildings. Authors in [35] proposed an isovist drift [15] agent with a three-dimensional field of view and an internal representation of the environment to simulate wayfinding in the vertical. A validation experiment with 69 human participants confirmed significantly less differences in wayfinding behavior between isovist-drift agents' and human behavior when compared to a shortest-path agent analysis. Nonetheless, the complexity of the wayfinding task in this study was minimal, requiring participants to find a door with a randomized color. Such task structure does not account for directed wayfinding tasks towards semantically defined destinations (e.g., looking for an office). Simulating these types of tasks is critical to inform wayfinding evaluation in buildings as one of the main tasks in the design process is the functional allocation of spaces in the building. Accordingly, it is necessary to model the background expectations people may have concerning the location of typical building destinations (e.g., entrance, exit, nurse station, office, roof terrace). Previous studies show that background expectations are applied to associate perceived environmental cues (e.g., configuration, materials, objects, people, and activities) with the locations of typical building destinations. For instance, an auditorium, main exits and restrooms are associated with more central and public locations whereas a rear exit, entrance to the cellar, and broom closet are associated with peripheral locations [53].

A more extensive vision-based cognitive agent that overcomes these limitations and integrates visibility, memory, background expectations and wayfinding strategies is proposed by authors at [38] who developed cogARCH. The latter is used to simulate directed wayfinding in multilevel buildings using vision-based cognitive agents and a hierarchical navigation space generated from a BIM representation. This hierarchical space consists of (1) a grid graph to represent the walkable space (2) an isovist grid to represent the qualities of the perceived space (3) a 3D representation of semantic activity zones and (4) a graph representing the connectivity between thresholds (e.g., doors, transitions between areas) that link the different activity zones in the building. Agents have a 3D field of view to perceive visual information from the environment. As agents move in the building, they develop an internal graph representation of visible and visited spaces (i.e. memory). The memory decays over time using a decay function. Agents can act upon the perceived sensory input using a range of wayfinding strategies (e.g., direction, floor, central point and perimeter strategies [11]) that correspond with their background expectations concerning the location of a destination or local cues that may be indicative to find a path towards it [53].

In summary, cognitive modeling holds great potential to inform wayfinding evaluation in architecture. Yet, and in contrast to this work, these studies have the following deficits with regards to their applicability to simulating wayfinding in AEC: (1) they mostly focus on modeling cognitive maps' [59] and overlook the well-known role of visual perception to inform wayfinding, especially in complex and multilevel buildings [11,35]. In such a setting, the visual perception (or lack thereof) of destinations or cues that are not accessible (e.g. a destination viewed through an atria on another floor) may trigger specific wayfinding strategies that should be modeled. (2) Visibility is reduced to capture a 2D field of view that is not appropriate to model the complex interplay between volumetric configuration and visual perception in multilevel buildings (except for a few notable exceptions that are restricted to simulate wayfinding by means of signage perception [79,80].) In addition, even if visibility is modeled, agents lack the cognitive mechanisms required to find their way on the basis of the visual information perceived (e.g., a 'cognitive map', strategies, commonsense knowledge). (3)Background expectations concerning the location or cues associated with semantically-defined destinations are not modeled, despite evidence showing its significant effect on wayfinding decisions [53]. In AEC fields, the need to simulate how the spatial organization of building functions affects wayfinding is a primary concern [82]. Therefore, it is cardinal to model agents' background expectations to provide meaningful simulation output to inform the design and operation of buildings.

3. Towards cognitive occupancy modeling in BIM

To move beyond direct routing, we propose a novel paradigm entitled Cognitive Occupancy Modeling in BIM. The proposed paradigm highlights the potential of combining cognitive modeling and semantically-enriched navigation spaces generated from BIM to inform agents' perception and cognitive-based decision making. On the basis of available evidence and theory we provide a high-level outline of agents' cognitive functions and the environmental layers required to support wayfinding decisions and simulate cognitively plausible wayfinding behavior.

Furthermore, we draw a conceptual link between BIM and the proposed environmental description, suggesting which information should be used to generate the navigation space. This includes the 3D geometry, information on building elements, material, and division to spaces and zones. This information is used to generate the necessary environmental layers required to form a hierarchical navigation space that corresponds with the agents' coarse to fine decision making structure [11]. These layers include a representation of the walkable space, the topological connectivity between spaces, the semantics of spaces and objects, the configurational properties of the visible space and the volumetric representation of functional areas. Agents' cognitive functionalities include vision, commonsense knowledge, memory and learning, wayfinding strategies, local heuristics and movement abilities. This hierarchical representation of the navigation space provides complex perception input for the agent. This input is then processed using agents' cognitive abilities, yielding cognitive-based wayfinding actions, such as strategic search towards non-visible destinations, local decisions following wayfinding heuristics, short-cutting and movement in the shortest path towards visible destinations or local goals.

An overview of the differences between the proposed paradigm and direct routing in the context of architectural design is provided in Fig. 1. The diagram maps both paradigms to the classical perception-action cycle [60] and highlights the key differences between the two paradigms. These relate to the type of building information inputs used to generate the environment, how the environment is represented, how agents perceive the environment, and how they may act in it.

4. Methods

To test the feasibility of the proposed paradigm, we conduct two interrelated studies. The first simulation study compares wayfinding performance of vision-based cognitive agents and direct routing agents under three building conditions with systematic variations applied to a multilevel building. To assess which agent model (cognitive agents' versus direct routing agents) better corresponds with human wayfinding we conduct the second study in which we perform a wayfinding experiment in VR with 149 participants. The methods and results of these experiments are presented in the following sub-sections.

4.1. Study 1 - agent-based simulation experiments

4.1.1. Agents

The simulation experiments included two types of agents; (1) Shortest-path agents (S) that perform direct routing using an A* algorithm applied to a grid graph representation of the walkable space, (2) Vision-based cognitive agents (C) that perform wayfinding using search strategies and background expectations on the basis of visual input captured from a hierarchical navigation space. Simulations were conducted using cogARCH, a software implementation developed in [38].[1]

4.1.2. Materials

Fig. 2 (Experimental setup), shows the three building scenarios included in the simulation experiments. The Base-case building spans 5 building floors. The building program consists of a cafeteria, exhibition space, auditorium, classrooms, open-space study areas, office spaces, meeting rooms, indoor patios, and a roof terrace. Vertical circulation between floors is enabled by two staircases and two elevators, all of which are located in enclosed concrete shafts. The buildings' main entrance is on the ground floor. The Base-case building is modeled after the Zollverein School of Management and Design in Essen, Germany, designed by SANAA architects.

Two variations on the Base-case building (i.e., Scenario 1) are introduced. One variation, Scenario 2, introduces five small-scale atria on the second floor similar to those on the fifth floor. We refer to this scenario as Atria. The other variation, Scenario 3, replaces the concrete enclosure of both circulation shafts that include staircases with a glass facade. We refer to this scenario as Glass. The proposed variations aim to make wayfinding in the Base-case building more efficient by increasing vertical visibility between floors. Architectural changes are intentionally applied to the three-dimensional configuration of the building. This is done to demonstrate the need for a vision-based cognitive agent to capture the potential effects these variations may have on wayfinding performance, and could not be observed using a shortest-path agent without vision or wayfinding strategies.

4.1.3. Wayfinding tasks

For both agent types, we consider typical wayfinding tasks for novice occupants. These tasks assume the same initial origin zone (i.e., the buildings' main entrance) combined with one of six semantically defined destinations (i.e., Auditorium, Reading Area, Study Area, Office, Patio, Roof Terrace). The initial heading of the agents has been randomized and a total of 3600 samples were generated. Simulations were executed through singularity-based containerization in a large-scale computing cluster.

4.2. Study 2 - a wayfinding experiment in virtual reality

4.2.1. Virtual reality setup

In the present study our aim was to analyze how changes in the configuration of buildings affect human wayfinding performance, and compare it against wayfinding performance of the proposed cognitive agents and classical direct routing agents. Isolating the effect of architectural configuration on wayfinding in a real-world experiment would have been difficult or even impossible, both with respect to the feasibility of applying systematic variations to the building, and with regards to the control of extraneous variables such as crowd density or signage [29,83].

Over the last two decades, the use of Virtual Reality (VR) to overcome the limitations of wayfinding experiments in RE has been increasingly adopted in AEC and in spatial cognition [31,84]. Unlike RE, VR is conducted in a controlled lab setting, and participants' interaction with the virtual environments such as walking trajectories, speed, head movement and gaze can be accurately recorded and captured for further analysis [31]. Several studies compared wayfinding behavior between RE and VR. Conroy-Dalton [85] compared movement patterns of people in a real art gallery and a virtual replica. A comparison of cumulative flow counts recorded in both the real and virtual building suggests a strong correspondence between flow counts. Pramnik et al. [86] compared participants' wayfinding in a real and virtual environment, displaying a correspondence in the average use of corridors, the average use of intersections, and wayfinding completion rates. Skorupka et al. [87] compared wayfinding in a real and virtual complex office building, suggesting that people may use similar cues or wayfinding strategies to find their way during real and virtual wayfinding.

Nonetheless, some differences between wayfinding in VR and RE have been reported as well, namely distance estimation in VR may be

[1] For a more complete description of cogARCH please refer to [38], DOI: http://simaud.org/2020/proceedings/10.pdf

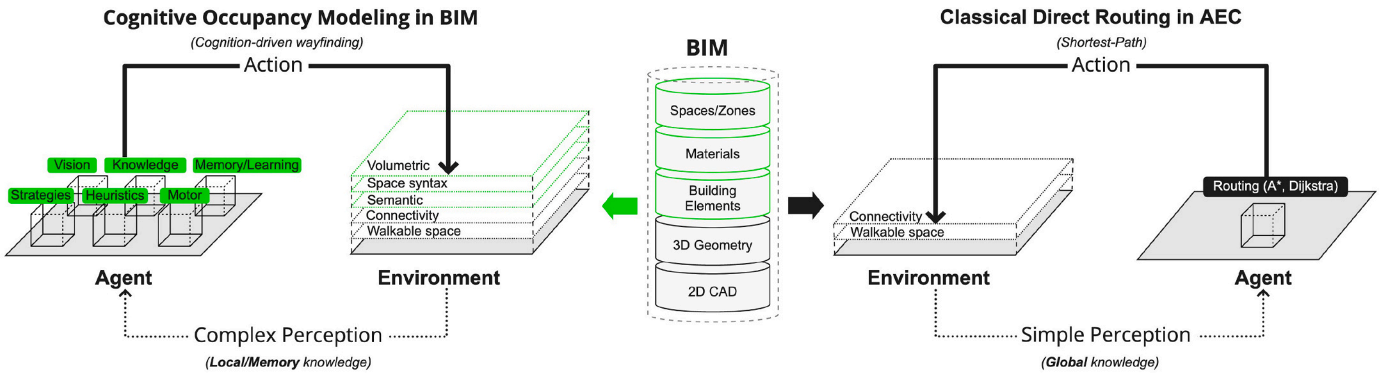


Fig. 1. Cognitive Occupancy Modeling in BIM versus Classical Direct Routing in AEC. The diagram maps both paradigms to the classical perception-action cycle [60] and highlights (in green) which cognitive aspects should be modeled as part of the agent or the environment to simulate cognitively plausible wayfinding. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

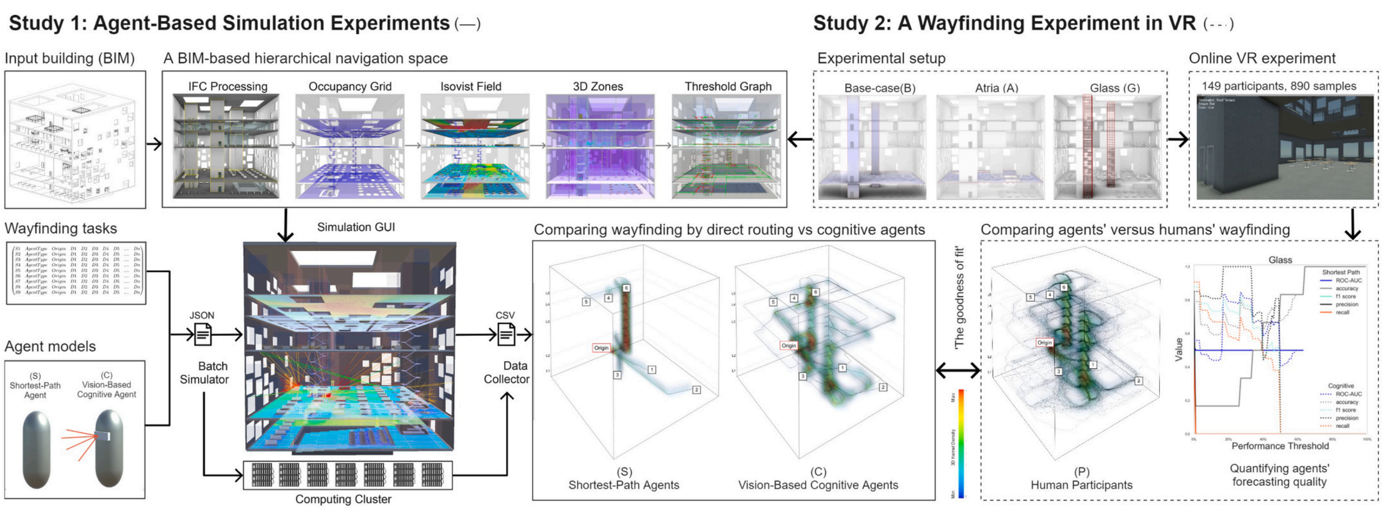


Fig. 2. An overview of the two interrelated studies. On the left: (1) The agent-based simulation experiments and the resulting analysis comparing wayfinding of cognitive agents (C) and shortest-path agents (S) (i.e., direct routing agents). On the right,(2) The wayfinding experiment in Virtual Reality with 149 participants and the comparative analysis between participants (P) and agents wayfinding under respective building conditions.

less accurate than in RE [88]. Moreover, whereas in RE spatial information is encoded in the brain during real physical self-movement [89,90], in VR, participants move by means of visual motion often using a keyboard and mouse [90]. Methods to integrate physical motion (e.g., walking) in VR include omnidirectional treadmills which may be sufficient for producing realistic locomotion behavior, but can also distract from the task without a large amount of training with the interface [91]. In contrast, mouse-and-keyboard interfaces use a completely different set of effectors (i.e., hands instead of legs) but are sometimes less distracting because of participants' familiarity with desktop computers [91]. Taking into account the considerable evidence suggesting that wayfinding in VR and RE is comparable, we chose to conduct the study using VR.

4.2.2. Participants

149 participants in total were recruited using Amazon's Mechanical Turk (Mean age = 33.7 years; SD = 6.8 years; Age range = 18 to 59 years). The study was approved by the Research Ethics Committee of ETH Zurich (2020-N-24) and all methods and experiments described in this paper were performed in accordance with the relevant guidelines and regulations. The main inclusion criteria were English proficiency, normal or corrected-to-normal vision, and ability to discriminate colors (i.e., color blind individuals were excluded). All participants signed an informed consent form before starting the experiment. Participants required approximately 20 min to complete the experiment and were compensated between 4.5 and 5.5 USD (mean = 5.4 USD) for their participation.

4.2.3. Materials

Study materials included the digital BIM models of the aforementioned building conditions used as part of the agent simulation experiments (See Fig. 2). The experimental software and processing of the virtual environment was developed using Unity3D game engine (Unity Technologies). BIM models were exported in an IFC format and imported to Unity3D using Tridify, an online cloud service that converts IFC models to Unity game objects while maintaining the semantic data encoded in IFC classes. To load the virtual buildings onto to the web, we used Unity's WebGL to render the environment in a web browser. Amazon's Mechanical Turk (MTURK) platform was used to recruit and reward participants. Trajectories were recorded by logging participants' positions and orientations every 0.02 s. Data was streamed in real time (4.3Kb chunks) to an online server and stored there until the end of the experiment. Participants had a first person view of the navigation environment and could navigate using a keyboard and mouse. Virtual movement included three degrees of freedom: forward/backward translations, left/right translations, and left/right rotation. To simplify the control setup, a homogeneous virtual character was assumed as reported in [92] (height = 1.8 m, maximum forward walking speed = 1.3

m/s; backwards and lateral moving speed = 0.6 m/s).

4.2.4. Procedure

Participants were randomly assigned to one of the three building scenarios. Each participant was first asked to digitally sign a consent form, to read the information page that introduced the task, and to complete a training phase to become familiar with the main task and the navigation control keys. The training phase took approximately 5 min, during which participants learned how to navigate in the virtual environment by completing a step-by-step tutorial meant to practice all possible movement options, including movement between floors by means of stairs. The environment used for training consisted of a simple multilevel building with two stair flights connecting the two levels. This environment was different from the one used in the following test trials to avoid any learning bias.

Upon successful completion of the training phase, participants were asked to perform a set of 6 wayfinding tasks (i.e., 1 task per trial). Participants were instructed to find a semantically defined destination (e.g. 'office'). The decision to ask participants to find a generic destination was intended to have them search the building using their background expectations (coupled with visual information). This approach provides a more comparable behavioral output to analyze humans' versus agents' behavior, given that the vision-based cognitive agents are partly driven by background expectations to inform strategy selection. Given that the destinations across tasks referred to a generic function and not to a specific instance (i.e., there could be multiple instances of a semantically-defined destination in the building), participants were told that the destination would be marked with a colored ball. The color of the ball was randomly generated per trial from a preset list of colors. Participants' origins across building scenarios and tasks were identical and set to the main entrance on the first floor (same as agents' origin) across tasks. To prevent any bias due to fatigue or learning, the task order was randomized. Exemplary screenshots from the VR study and the training tutorial are provided in the Supplementary Materials.

5. Results

5.1. Study 1: comparing wayfinding performance between cognitive and direct routing agents

The analysis of the simulation results aims to quantify the differences in observed wayfinding behavior between cognitive and shortest-path agents, across tasks and between scenarios. Accordingly, we performed the following analyses: (1) A Kernel Density Estimation (KDE) to visually inspect potential differences in the density distribution of agents' trajectories across tasks and building scenarios;(2) multiple Linear Mixed Effects Model Regressions (LMEMR) [93] to quantify the difference in subject's average distance performance between the Base-case building (B) and either the Atria (A) or Glass (G) scenarios (see Table 1); (3) a forecasting quality analysis that considers the agent models as binary classifiers with varying classification thresholds to compare the 'forecasting power' of the two agent models, specifically focusing on its capacity to forecast improvement in average distance performance as a function of architectural design variations.

Table 1
Linear Mixed Effects Model Regressions (LMEMR) design. A total of 6 different LMEMRs are used to analyze the effect of the systematic architectural variations on the subjects' wayfinding distance performance. This analysis evaluates individually either the shortest-path agents (S), the cognitive agents (C) or the participants (P) against a building comparison pair, i.e., Base-case versus Glass (B-G) or Base-Case versus Atria (B-A), considering the building as the fixed effect and the task as the random effect.

Distance performance ~ fixed effect (building) + random effect (task)			
Subjects	(P)	(C)	(S)
Comparison Pairs	Human Participants	Vision-Based Cognitive Agents	Shortest-Path Agents
Base(B)-Glass (G)	#1 P(B-G)	#2C(B-G)	#3 S(B-G)
Base(B)-Atria (A)	#4 P(B-A)	#5C(B-A)	#6 S(B-A)

We begin by comparing the spatial density and distribution of agents' trajectories between scenarios. Fig. 3 shows the results of this analysis performed using 3D Kernel Density Estimation (KDE). It can be observed that path density in shortest-path agents (see Fig. 3a), is highly localized and shows minimal variability across scenarios in comparison to cognitive agents (see Fig. 3b, c, d). These results are further reflected when comparing the average distance performance between cognitive and shortest-path agents across 6 wayfinding tasks, as can be seen in Fig. 7a and Fig. 7b. Whereas shortest-path agents showcase minimal performance variability, cognitive agents' performance varies largely between scenarios.

To analyze the effect of the architectural variations on agents' wayfinding distance performance while accounting for the random effect of the wayfinding task (i.e., considering the substantial variance in distance performance, see Fig. 7a, b) we focus on four LMEMRs. These four LMEMRs (out of the six LMEMRs, see Table 2) are the ones related to the agents (i.e., LMEMR #2, #3, #5, and #6). The two remaining LMEMRs (i.e., LMEMR #1 and #4), relate to the human participants and are discussed in the next section alongside additional measures.

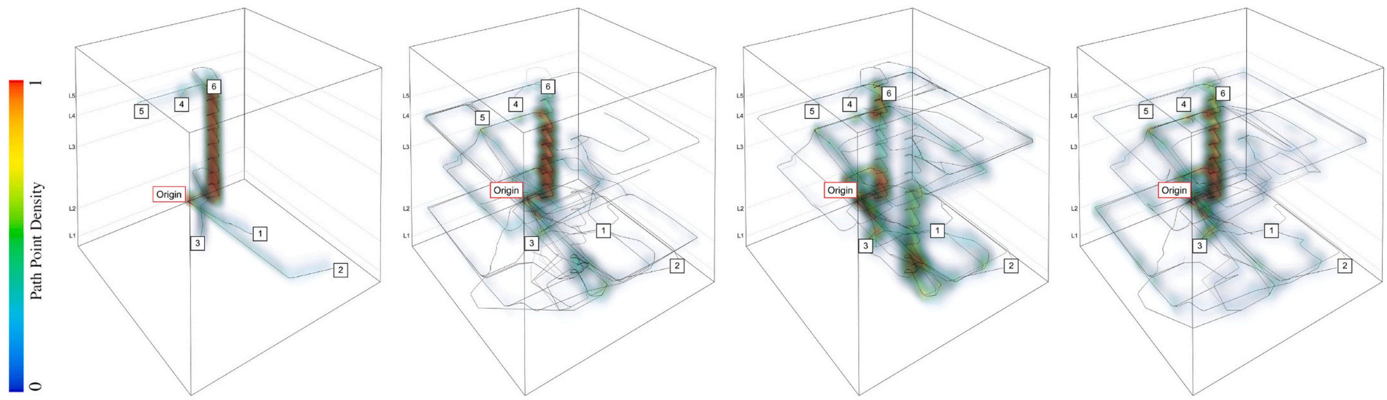
As can be seen, LMEMR model #3 and LMEMR model #6 show that both architectural variations (i.e. Glass (G) and Atria (A)) had a marginal effect on shortest-path agents' performance when compared to the Base-case scenario (B). In both scenarios, the shortest-path agents' subjected to the same random initializations displayed a minimal increase in the path length; 0.230 m in the Glass scenario (G) and an even more negligible distance increase in the Atria (A) scenario (0.051 m); In contrast, LMEMR #2 and LMEMR #5 show that the same architectural variations (i.e. Glass (G) and Atria (A)) had a substantial effect on cognitive agents' wayfinding performance. More specifically, cognitive agents display a substantial improvement in distance performance (i.e., decrease in distance covered across tasks) of 110.328 m from the Glass (G) to the Base-case scenario (B) and 87.290 m for the Atria scenario (A).

5.2. Study 2: comparing humans' versus agents' wayfinding performance

The analysis of the experimental data focused on quantifying the differences between both agent types and human participants for respective building conditions and tasks. Our aim was to uncover which of the two agent models better captures the effect of the architectural variations on wayfinding, when compared to human wayfinding observed in the VR experiment under respective building conditions.

Our analysis included a total of 890 samples from the VR experiments. An overview of agents' versus participants' trajectories for each of the three scenarios is presented in Figs. 5 and 6. Similarly to the analysis of the agent-based simulation results, we analyze the density of participants' trajectories across building conditions as well as the difference in participants' distance performance from the Base-case (B) scenario to the Atria (A) and Glass scenario (G). Results of these analyses are then compared to the corresponding findings per agent type (i.e. shortest-path agents versus cognitive agents).

We begin by calculating the spatial density and distribution of participants' trajectories (Fig. 4) for each building scenario using 3D Kernel Density Estimation (KDE). Inspecting these results (i.e., Fig. 4) highlights two notable findings: (1) A marked difference between density patterns is observed between building conditions, suggesting that the architectural variations had a substantial effect on participants' spatial search behavior, and (2) participants' path density across the Base-case (Fig. 4a) and Atria (Fig. 4b) conditions was substantially more dispersed when compared to the Glass scenario (Fig. 4c), where density patterns converged to the area of the circulation core that was closer to the main



(a) Shortest-path agents, across scenarios (b) Cognitive agents, Scenario 1.(Base-case) (c) Cognitive agents, Scenario 2. (Atria) (d) Cognitive agents, Scenario 3. (Glass shafts)

Fig. 3. Overlay of agents' paths (shortest-path and cognitive) with 3D path point Kernel Density Estimation (KDE) across tasks and building scenarios.

Table 2
Results of 6 Linear Mixed Effects Model Regressions (LMEMR) quantifies the effect of the building scenario (Base-case (B), Atria (A), Glass (G)) and group (Participants (P), Shortest-Path agents (S), Cognitive agents (C)).

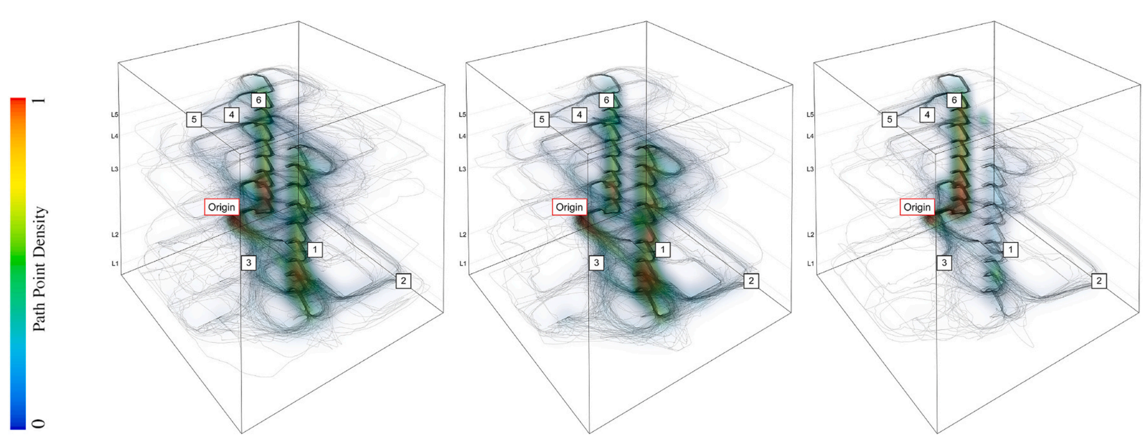
# Regression	Effect	Coef.	Std.Err.	z	*p*-Value
1 *Dist* ~ *Buil.* P(B-G)	buil.	−64.622	11.799	−5.477	p<0.01
2 *Dist* ~ *Buil.* C(B-G)	buil.	−110.328	3.944	−27.975	p<0.01
3 *Dist* ~ *Buil.* S(B-G)	buil.	0.230	0.015	15.136	p<0.01
4 *Dist* ~ *Buil.* P(B-A)	buil.	−14.472	12.268	−1.180	0.238
5 *Dist* ~ *Buil.* C(B-A)	buil.	−87.290	3.477	−25.107	p<0.01
6 *Dist* ~ *Buil.* S(B-A)	buil.	0.051	0.026	1.957	0.050

entrance. When comparing participants' density patterns to those of shortest-path agents'(Fig. 3a) across building conditions, a striking difference is crystallized, revealing a sharp contrast between the highly localized and invariant density patterns of shortest-path agents and the substantially varied density patterns of participants' trajectories across building conditions.

Differently than shortest-path agents, cognitive agents present a considerably more comparable density pattern to that of human participants, both with regards to variability across scenarios and regarding the observed convergence pattern in the case of the Glass scenario 4c. Nevertheless, the similarity between participants' and cognitive agents' density patterns is still lacking in some respects, pointing to the limitations of the cognitive agent model that would be further evaluated in the discussion section.

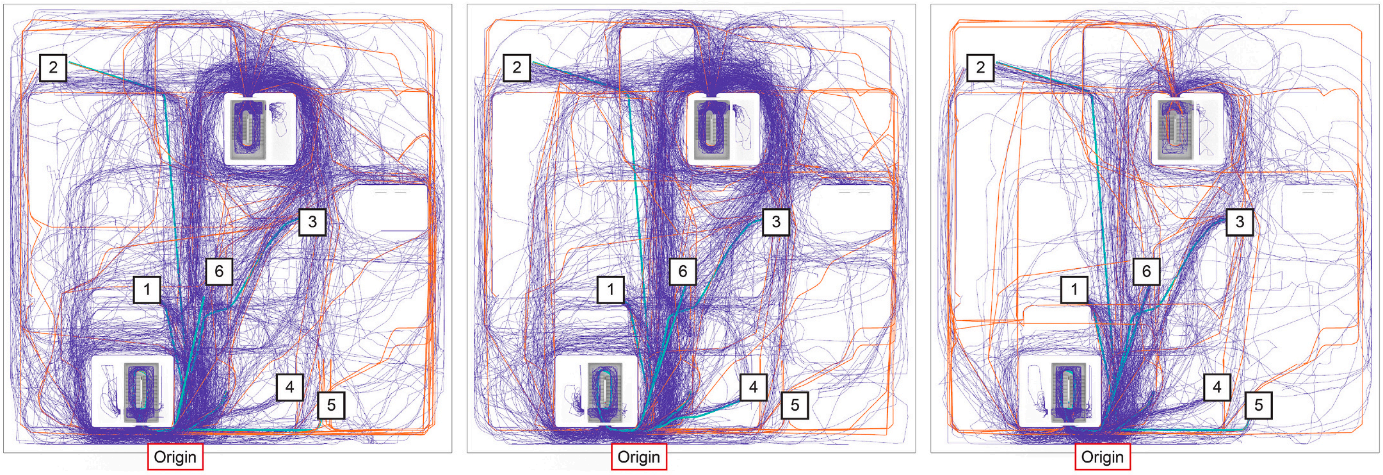
To provide a quantitative comparison between participants' and agents' behavior, we performed multiple LMEMR analysis, as presented in Table 2. This analysis aims to quantify the effect of the building variation on participants' performance, comparing the performance sampled across pairs of conditions, between the Base-case and the Glass condition (i.e. B-G), and between the Base-case and the Atria condition (i.e. B-A). Results of the LMEMR #1 and LMEMR #4 demonstrate a statistically significant improvement in distance performance in the Glass and Atria conditions when compared to the Base-case ($p < 0.01$); LMEMR #1 suggests that the architectural variations applied, resulted in participants' walking on average 64.622 m less in the Glass condition (G) when compared to the Base-case (B), and LMEMR #4 indicates that variations applied in the Atria condition (A) resulted in participants walking in average 14.472 m less in comparison to the Base-case condition (B), all while controlling for the different tasks.

Whereas a more in-depth analysis of participants data is required to fully understand the underpinnings of their behavior, a comparison of the LMEMR results between agents and participants marks a clear trend; whereas shortest-path agents displayed an increase in distance performance across building conditions, participants and cognitive agents alike presented a comparable decrease in distance performance between the Base-case and Glass scenarios (Participants; −64.622 m, Cognitive



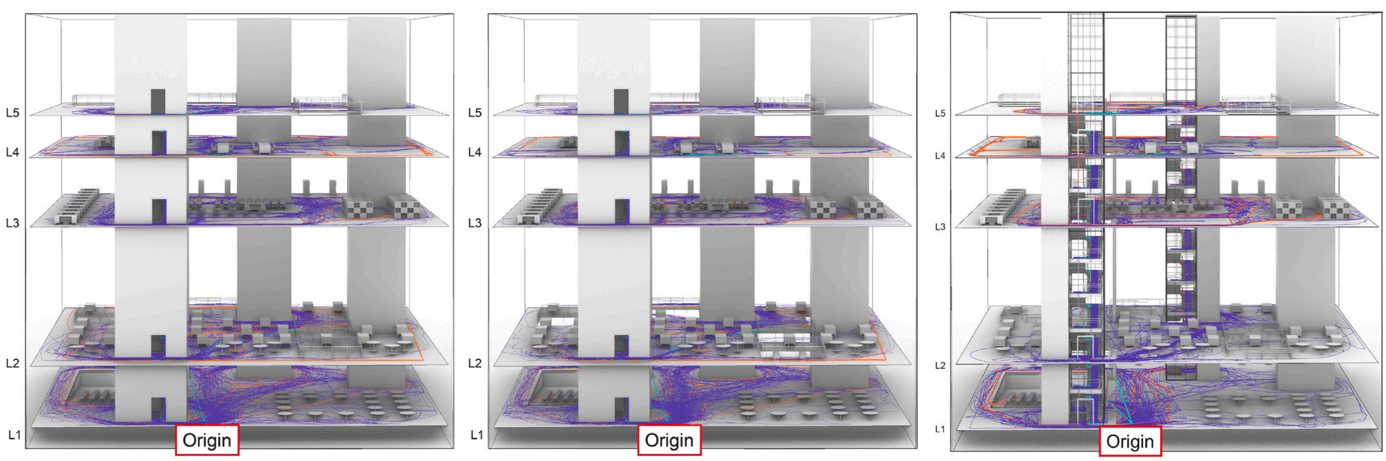
(a) Participants Scenario 1.(Base-case) (b) Participants Scenario 2.(Atria) (c) Participants Scenario 3. (Glass shafts)

Fig. 4. Overlay of human participants paths sampled in the VR experiment, with 3D path point Kernel Density Estimation(KDE) across tasks and building scenarios.



(a) Scenario 1: Base-case (b) Scenario 2: Atria (c) Scenario 3: Glass

Fig. 5. Planar projection of agents and participants trajectories across building scenarios (–, Shortest-path agents), (–, Cognitive agents), (–, Participants)



(a) Scenario 1: Base-case (b) Scenario 2: Atria (c) Scenario 3: Glass

Fig. 6. An overlay of participants' and agents' trajectories onto the 3D model of each building scenario (–, Shortest-path agents), (–, Cognitive agents), (–, Participants).

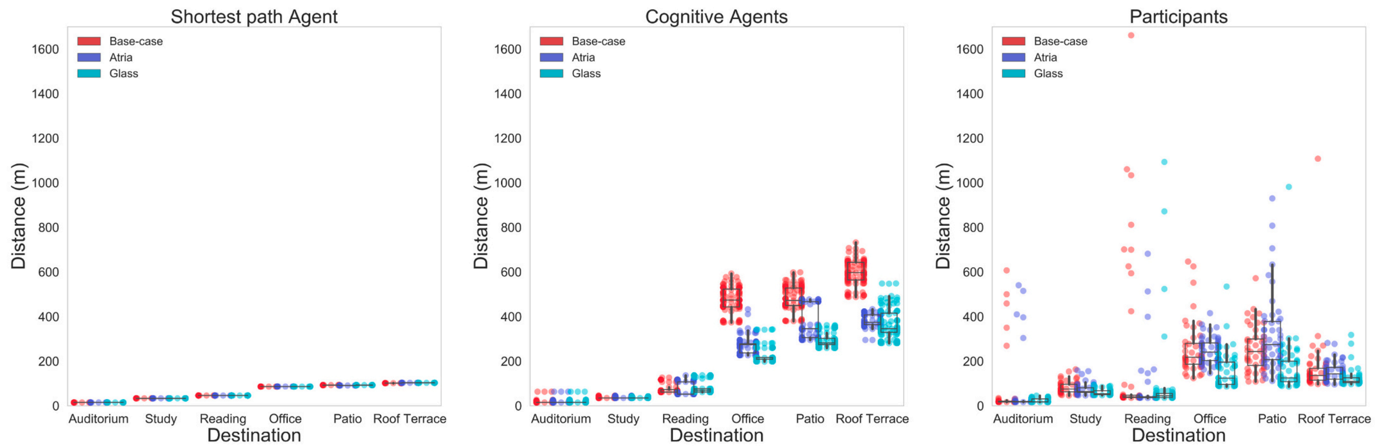
Agents; −110.328 m), and between the Base-case and Atria condition (Participants'; −14.472 m, Cognitive Agents; −87.290 m).

Notably, overall, cognitive agents actually performed wayfinding less efficiently than human participants, and covered more distance to find their way across all building conditions, see Fig. 8a and Fig. 7b and c in which distance performance across destinations and groups (shortest-path agent, cognitive agent, human participants) is presented. However, in terms of relative improvement between building conditions (e.g., Base-case versus Atria and Base-case versus Glass), cognitive agents indeed showed greater relative improvement between conditions in comparison to human participants. The reason for this is that human participants were more efficient than cognitive agents in the Base-case scenario (i.e., walked less to find their way), resulting in greater improvement potential than that of cognitive agents.

Lastly, we aim to evaluate which of the two agent models better forecasts the observed improvement in participants' average distance performance between the Base-case scenario and each of the buildings to which we applied architectural variations (i.e. Atria and Glass). This analysis is done by considering a simplified binary classification problem, in specific: improvement (1) or no improvement (0). For more details on the classification method used please see the Supplementary Materials.

Fig. 8b and c, show these metrics as a function of the 'performance threshold', the gray rectangle in both figures marks that above (>70%) there is no improvement across both models. As expected, the cognitive agent outperforms the shortest-path agent in every metric for most of the thresholds. It has to be noted that as the threshold increases, less improvement is considered in the ground truth (i.e. participants). In turn, the shortest-path agent becomes a more accurate model as it consistently returns a 'no improvement' classification. This is an artifact of the analysis construction that, as noted above, should avoid low and high values of the 'performance threshold'. Yet, for completeness, we decided to present the full threshold range.

Interestingly, cognitive agents were considerably more predictive in the Glass scenario 8c than in the Atria scenario 8b, when compared to shortest-path agents. This finding corresponds with the findings from our LMEMR analysis showcasing that participants performance was significantly ($p<0.01$) differing in the P(B-G) comparison and not in the P(B-A) comparison, meaning that participants wayfinding was more efficient in the Glass condition when compared to the Base-case scenario.

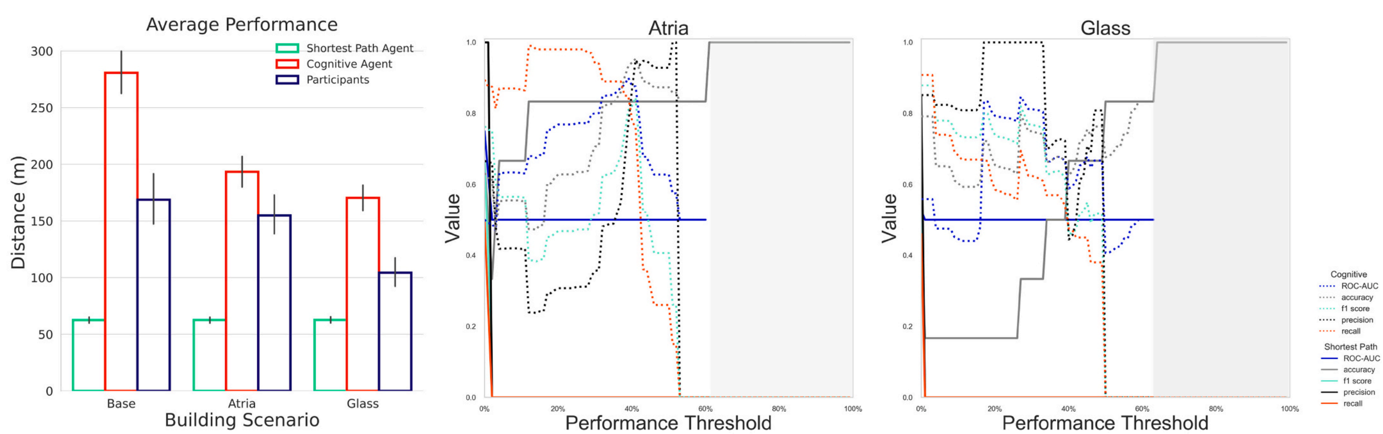


(a) Shortest-path agents' average distance performance across 6 wayfinding tasks for each building scenario

(b) Cognitive agents' average distance performance across 6 wayfinding tasks for each building scenario

(c) Human' participants average distance performance across 6 wayfinding tasks for each building scenario

Fig. 7. Differences in average distance performance between human participants', cognitive agents' and shortest-path agents' for each task and across building scenarios.



(a) Average performance comparison for all tasks and between scenarios for both agent types and participants

(b) Average forcasted improvement in distance performance between the Base-case scenario and the Atria scenario (in %)

(c) Average forcasted improvement in distance performance between the Base-case scenario and the Glass-shafts scenario (in %)

Fig. 8. Quality metrics considering the two agent models (shortest-path versus cognitive) as a binary classifier with varying classification threshold to compare the 'forecasting power' of the two agent models, considering each models' capacity to forecast improvement in average distance performance as a function of architectural design variations.

6. Discussion and conclusion

"Able or not, today's architects.....have an enormous impact on the wayfinding success or failure of a setting. In planning the layout, they are creating the setting and the wayfinding problems future users will have to solve…" [94]. As this quote by Paul Arthur and Romedi Passini reflects, architectural design and wayfinding are fundamentally intertwined. Nevertheless, during the design process they are largely disconnected. The responsibility to guide people in buildings is effectively delegated to signage designers, limiting the potential of architecture to shape wayfinding experience by means of configuration, functional allocation and materiality. This disconnect is further reflected in current simulation approaches in AEC that overlook the cognitive aspects of wayfinding and instead formulate this process as a shortest-path problem which cannot capture the complex interplay between architecture and wayfinding, nor its outcomes.

To bridge the disconnect between wayfinding and architecture, the work presented in this paper combines advances in cognitive modeling, concepts from vision-based robotics and BIM with evidence and theory from cognitive science. We present a holistic modeling paradigm entitled Cognitive Occupancy Modeling in BIM that puts forth a blueprint for modeling wayfinding by cognitive agents in BIM. In contrast to direct routing agents, the proposed paradigm highlights the necessary cognitive processing mechanisms (e.g.,vision, wayfinding strategies, memory, learning, and commonsense knowledge) and environmental information (e.g., metric, semantic, volumetric, topological and connectivity information) required to simulate wayfinding in a cognitively plausible manner.

To critically assess the proposed paradigm against classical direct routing, we conducted two interrelated studies. The first simulation study compares the variability in wayfinding behavior observed by vision-based cognitive agents and direct routing agents under three building conditions with systematic variations applied to their volumetric design. These variations manipulate the degree of visibility between floors through systematic architectural design actions (e.g., introducing atria between floors or varying the transparency of building surfaces). To assess which agent model (cognitive agents' versus direct routing agents) better corresponds with human wayfinding we conducted the second study in which we performed a wayfinding experiment in VR with 149 participants.

Results from the first simulation study provide convincing evidence of the proposed Cognitive Occupancy Modeling in BIM paradigm to reflect significant variability in agents' behavior as a result of architectural design variations. This variability stands in contrast to the statistically invariant wayfinding behavior of classical direct routing agents (i.e. shortest-path agents) in response to the same architectural changes. Results from the second study included a total of 890 wayfinding tasks by human participants under the same experimental setup used for the first study. Our analysis compared human wayfinding to that of both agent types. Results mark a clear trend; whereas shortest-path agents' displayed an increase in distance performance across building conditions, participants' and cognitive agents alike presented a comparable decrease in distance performance between the Base-case and Glass scenarios (Participants; −64.622 m, Cognitive Agents; −110.328 m) and between the Base-case and Atria condition (participants; −14.472 m, Cognitive Agents; −87.290 m).

These results indicate a substantial correspondence between participants' and cognitive agents' wayfinding behavior, whereby increased vertical visual connectivity resulted in a substantial decrease in distance performance. In sharp contrast, the wayfinding performance of shortest-path agents was almost invariant to the same architectural variations, displaying an opposite effect. This is further reflected in the results of a concluding evaluation comparing which of the two agent models better forecasts the observed improvement in participants' average distance performance between the Base-case scenario and each of the buildings to which we applied architectural variations (i.e. Atria and Glass). Specifically, the results show that vision-based cognitive agents outperform the shortest-path agents in every metric for most of the thresholds and are therefore considerably more predictive when compared to shortest-path agents.

Notably, and although a solid body of evidence suggests that wayfinding in VR and Real Environments(RE) [92,95,96] are indeed comparable, the limitations of VR to fully capture wayfinding in RE should be considered when interpreting our results. Namely, distance estimation in VR may be less accurate than in RE [88], and the use of visual motion (as opposed to physical motion) may affect neural encoding of spatial information in memory [90].

To our knowledge, this paper is the first attempt to compare direct routing agents, cognitive agents and observed human behavior for the case of wayfinding in multilevel buildings, and considering architectural variations related to vertical visual connectivity. The vision-based cognitive agents were able to better capture the variability in wayfinding performance across conditions in a way that is comparable with human wayfinding behavior. We expect that further calibration of cognitive agents with human observations will improve the 'goodness of fit' of the proposed model when compared to human behavior. Whereas such parameter fitting is possible for the case of cognitive agents, it is not the case for shortest-path agents who lack a parameter space and operate on the basis of a uniform algorithm. Furthermore, we aim to initiate a critical and scientifically rigorous discussion on the development and validation of agent-based models for the AEC community.

Beyond fitting specific model parameters, there has been thriving research in the use of more adaptable models produced through machine learning techniques. For example, Artificial Neural Networks [97] have been used to model locomotion behavior and Reinforcement Learning (RL) has been increasingly used to solve routing problems [98], and even simulate wayfinding [67]. Although these studies have been limited to simple, single-level environments, there is a great potential for their application to multilevel and complex buildings as the ones considered in our work. Specifically, the use of RL to model uncertainty and learning through the provision of a reward signal offers a complementary mechanism to our theoretically-grounded cognitive agent model. Yet, completely adaptive models such as the ones provided by artificial neural networks contain parameters and hyper parameters (e.g., number of layers, weights of neurons, dropout ratios) that require more nuanced interpretation, when compared to agents with limited and meaningful parameters (e.g., preferred walking speed, view angles). We believe that machine learning, especially when combined with cognitive-modeling is a promising method to simulate human cognition. To fully realize this potential for the case of wayfinding, it is necessary to adopt a critical approach in which agents modeled using different methods are compared against one another, and against human behavior with respect to fit, but also with regards to the interpretability of behavioral parameters and emergent behavior.

6.1. Implications

The paradigm and method presented in this paper provides an integrated, iterative, validated and cost-effective way to forecast how architectural changes in a multilevel building (e.g., carving out an atrium, or changing the transparency of walls) will affect wayfinding performance measures (e.g., efficiency measures as distance covered to find a destination). Such insights could directly inform preliminary design stages and reduce various negative effects associated with getting lost [8,17]. As demonstrated in the Results section, direct routing algorithms used to calculate the shortest path assuming global knowledge of the environment were invariant to the same architectural changes. Notably, such direct routing agents (e.g., A*) are prevalent in commercial simulation tools used in AEC practice [23,56,57]. Yet, as our results show, such models are unable to account for how people find their way in unfamiliar buildings. This is especially problematic for the case of complex and costly buildings such as hospitals, museums, and transportation hubs. Our method, although requiring further refinements and additional validation, provides a novel alternative which could help practitioners design *wayfinding by architecture* from the very early stages of the design process.

6.2. Limitations and future work

Our novel findings concerning the forecasting capacity of wayfinding performance by direct routing agents and cognitive agents must be considered alongside the limitations of our approach. Notably, although the proposed cognitive agent was able to capture the direction of improvement (i.e., in wayfinding performance) presented by human participants, it had a limited capacity to capture the size of the improvement. As our comparative analysis shows, cognitive agents' relative improvement (i.e. in meters) between the base-case scenario and the other two building conditions was greater than that observed in the case of human participants. This means that human participants covered less distance and showcased more efficient wayfinding in the Base-case condition, such that their potential improvement was smaller to begin with. In this sense, cognitive agents were less efficient than the human participants in the base-case scenario which left more room for them to improve.

The potential reasons for cognitive agents covering more distance and finding their way less efficiently in the Base-case scenario when compared to human participants are numerous, and rooted in the simple fact that these agents are far less cognizant than any human being. In the present paper the proposed cognitive agents had a limited number of simplified strategies and background knowledge [38] to find their way whereas human participants with real human cognition (as opposed to simulated cognition) possess potentially more sophisticated strategies and richer background knowledge which they employed during wayfinding in the Base-case scenario. We conjecture that parameter tuning, fitting or training would help close this gap (e.g., [28]).

Accordingly, to improve the forecasting capacity of cognitive agents it is critical to model additional wayfinding strategies (e.g. [99]), richer background knowledge [34] and more elaborate memory models [67]. Towards this end, a follow up manuscript that provides an in-depth analysis of human participants' wayfinding in the VR study is underway. This paper will shed light on the relationship between wayfinding strategies in response to systematically applied changes in vertical visual connectivity, and analyze how individual differences (e.g., gender, age) may affect wayfinding performance and behavior. These findings may be used to inform future extensions of the proposed cognitive agents and advance our ability forecast how architectural design of complex, multilevel buildings affects wayfinding performance and behavior.

Data availability

The wayfinding dataset obtained in the VR experiment as well as data generated as part of the agent simulations is available in GitHub: https://github.com/MichalGath/DataWayfinding\ExperimentSimulationZollverein.git

Declaration of Competing Interest

The authors declare no competing interests.

Acknowledgements

This research was supported by a Swiss Government Excellence Scholarship (ESKAS No. 20NN.PPPP) and additional funding from the Chair of Cognitive Science at ETH Zurich.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.autcon.2022.104131.

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