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Technical Section

# AUTOSIGN: A multi-criteria optimization approach to computer aided design of signage layouts in complex buildings[☆]

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ABSTRACT

To improve the efficiency and effectiveness of designing signage systems in buildings, we present AUTOSIGN – a design tool that supports user-in-the-loop and multi-criteria optimization of signage layouts in complex buildings. We formulate signage placement as a multi-objective optimization problem with competing objectives (i.e., total distance travelled, total number of turns, the centrality of decision points, path overlap, and number of decision taken) and constraints (i.e., user-specified sign location and orientation threshold), which we solve using a two-step approach. Firstly, an evolutionary method is used to optimize all combination of navigation paths based on cognitively inspired objective functions weighted by the designers. Secondly, a particle swarm optimization is used to optimize individual sign placement to maximize the exposure of wayfinding information (i.e., signage coverage area) from the optimized navigation graph generated. To evaluate the effectiveness of the tool, we apply it to the design of signage systems across two virtual 3D buildings. We generate signage layouts for both buildings and optimize each of them for user-defined criteria. Both optimized and non-optimized layouts are evaluated using an agent-based simulation. The simulation results demonstrate that even with fewer signs, the signage coverage area for the optimized layout increased by 18% on average. Finally, an expert-based VR walk-through and a System Usability Study is performed to further evaluate AUTOSIGN.



## 1. Introduction

Signage systems play an essential role in facilitating occupants' wayfinding in complex buildings. A well-designed signage system reduces perceived spatial complexity of a built environment, thereby improving occupants' ability to find their way from an origin to a destination [1]. More importantly, during emergencies, signage provides essential information to help occupants evacuate through emergency exits and reach safe areas.

In the design of signage systems intended to support efficient and safe wayfinding, a central challenge is the positioning of signs in 'optimal' locations. In large and complex buildings with multiple entrances and exits, leading to multiple combinations of passageways and junctions, manual positioning of signs is a challenging, cumbersome and time-consuming design task. It is practically unfeasible to manually account for the myriad of possible wayfinding scenarios while considering various (often conflicting) design objectives; direct occupants along the shortest route (e.g. in the case of emergency), avoid redundancy of signs, maximize the visual catchment area (i.e., is the region in which an occupant can physically perceive wayfinding information from a sign [2]) of a sign with respect to the location of decision points, etc. Traditionally, signage evaluation and design are based on general guidelines, expertise, and paper mock-ups, all of which rely heavily on designers' intuition and experience.

More recently, Virtual Reality (VR) walk-throughs and spatial analysis methods have also been employed to inform manual signage design, and in particular signage placement. Despite their advantages, both methods are highly laborious and time-consuming, and yet, neither one is able to explicitly inform signage placement to improve the overall range of wayfinding scenarios, or visibility constraints due to the building configurations and human perception. Poor design of signage systems that conflicts with either the building design or human perception may cause stress, reduce

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wayfinding efficiency and pose a threat to the evacuees [3]. The effort required to manually design signage systems to account for all factors is considerable and can rapidly scale up in a complex building.

To improve the efficiency and effectiveness of designing signage systems in buildings, a computational approach that can automate the process of signage positioning and evaluation is necessary. This paper presents AUTOSIGN – a computer-aided signage design tool that supports a user-in- the-loop, multi-criteria-optimization of signage layouts in complex buildings. AUTOSIGN employs a multi-objective genetic algorithm for path optimization based on various cost functions followed by particle swarm optimization to determine the optimal sign placement based on visual coverage area.

The architectural design process of buildings consists of various stages, from preliminary design to construction. Throughout this process, the level of detailed information encoded in buildings' representation (i.e., floorplans, 3D BIM model) varies from highly abstract to highly detailed. To support informed signage design throughout the various stages of a building's design process, AUTOSIGN is intentionally designed with minimal input requirements. To that end, AUTOSIGN allows the users to control the level of detail at which the building geometry is exported (i.e., depending on the design stage). Once the building model is exported AUTOSIGN automatically generates an optimized signage layout onto the 3D model. The signage layout includes both the physical locations of signs in space and the directional information (arrows) corresponding to each sign. The tool provides the designer/user with the flexibility to manually translate and rotate the sign position and orientation.

The main deliverable of this paper is AUTOSIGN: an interactive user-in-the-loop design and optimization system for signage placement in complex mixed-use environments (e.g., transportation facilities, shopping malls). AUTOSIGN is powered by two main contributions: (1) an automated approach to extract wayfinding decision points from raw 3D building geometry to serve as the basis for estimating the wayfinding complexity of an environment. (2) Formulation of signage design as a two-step optimization process. First, we perform multi-objective optimization to select the most effective combination of route choice criteria to form a weight vector that produces routes between each pair of O-D. Second, we present a particle swarm optimization-based approach to determine an optimal sign positioning that maximizes signage coverage area.

To validate the effectiveness of the tool, we apply it to the design of signage layouts for two virtual 3D mixed-use buildings. Signage layouts for both buildings are first generated and then optimized for user-defined criteria by AUTOSIGN. Both optimized and non-optimized layouts are evaluated for occupants' wayfinding performance using agent-based-simulation and expert-based VR walk-through. We also evaluate the signage-design variations by systematically adjusting the relative influence of the proposed cost functions. Finally, the performance results from a System Usability Study with experts is presented.

## 2. Related work

The evaluation of signage systems in buildings is a complex task. Traditionally, signage evaluation and design are based on expert intuition, expertise, paper mock-ups or post-occupancy assessments [4]. More advanced methods include the use of spatial analysis tools to measure various visibility and inter-visibility related aspects (e.g. isovist, Visibility Graph Analysis (VGA) or Visible Catchment Area (VCA)) of a building layout or a proposed signage system [2]. Another approach uses immersive virtual environments, whereby experts 'walk-through' a virtual 3D model of a building to evaluate either the potential location of signs or the appropriateness of proposed signage layouts [5]. The work in [6] proposed a wayfinding simulation to evaluate the design of directional signage systems in 2D for evacuation purposes. The main shortcoming of this work lies in its simplified formulation of human vision, which fails to account for sign legibility and detection. These evaluation methods (i.e. spatial analysis, expert-based virtual walk-through, agent-based simulation) support the assessment of distinct aspects related to wayfinding employing sign-following. A VR walk-through performed by experts who simulates wayfinding from the perspective of potential occupants could be useful to provide a qualitative assessment of wayfinding performance (e.g. hesitation points). By having an expert conducting the walk-through, it may be possible to overcome the phenomena known as 'momentary suspension of disbelief' observed in lay participants who navigate in virtual environments with low-level of detail and realism [7]. In contrast, an agent-based simulation approach could provide a quantitative assessment of wayfinding performance given different signage layouts and varied user groups (e.g. walking distance) while considering many origin and destination pairs. These methods could be regarded as complementary to one another.

Lin et al. [8] proposed a method to optimize directional signs to facilitate occupants' wayfinding in a complex transportation terminal (i.e., airport terminal) using a mathematical model. The placement of signs was guided by a cellular automation model that accounts for environmental conditions, such as crowd conflicts and congestion conditions. Tam et al. [9] proposed a binary linear program for better allocation/placement of directional signs for wayfinding. In their study, they used a quantitative measure called visibility index (i.e.,the ratio of the number of sight lines that are available and the total number of sight lines that should exist within the terminal) for evaluating the ease of wayfinding. Recently, Zhang et al. [10] developed a system in which a minimum number of evacuation signs and their locations in a hall are determined automatically by using a cellular automata-based evacuee-signage interaction model. Similarly, Motamedi et al. [4] proposed an agent-driven signage optimization in a BIM-based 3D environment. Their proposed tool had predefined scenarios to compute signage coverage area and overall visibility of the buildings signage system. However, both approaches fail to account for (a) signage noticeability (b) spatial complexity of building layouts [10] and (c) inter-dependency between signage information received and codependent directional signs. [4] proposed an interaction between the Digital Human Model (DHM) and directional signage based on visual perception, driven by sign lo- cation, visibility, noticeability and legibility. Though they provide validation by conducting experiments, the small sample size (six), cannot be considered as a thorough and conclusive validation.

One common limitation among these methods is the separation of signage design generation and signage evaluation. To address this gap, AUTOSIGN provides a holistic approach that allows designers to iterate between signage design and evaluation. This approach is by no means a new one and is built upon a previously laid foundation of Computer Aided Architectural Design (CAAD), in which high-level goals and constraints are defined. Using the power of computation, a broad design space is automatically generated and evaluated in an iterative manner [11–14].

Recently, much attention is given to human-centred design methodology for proposing an easily walkable built-environment. Authors in [15] propose an integrated approach by bridging human factors with environmental factors. Factors such as visual, acoustic, and pedestrian thermal comfort are essential to be considered while designing a public space for easy and stress-free navigation. Authors in [16] proposed a crowdsourced indoor navigation system named SoleWay. In their work, they involved end-users of a

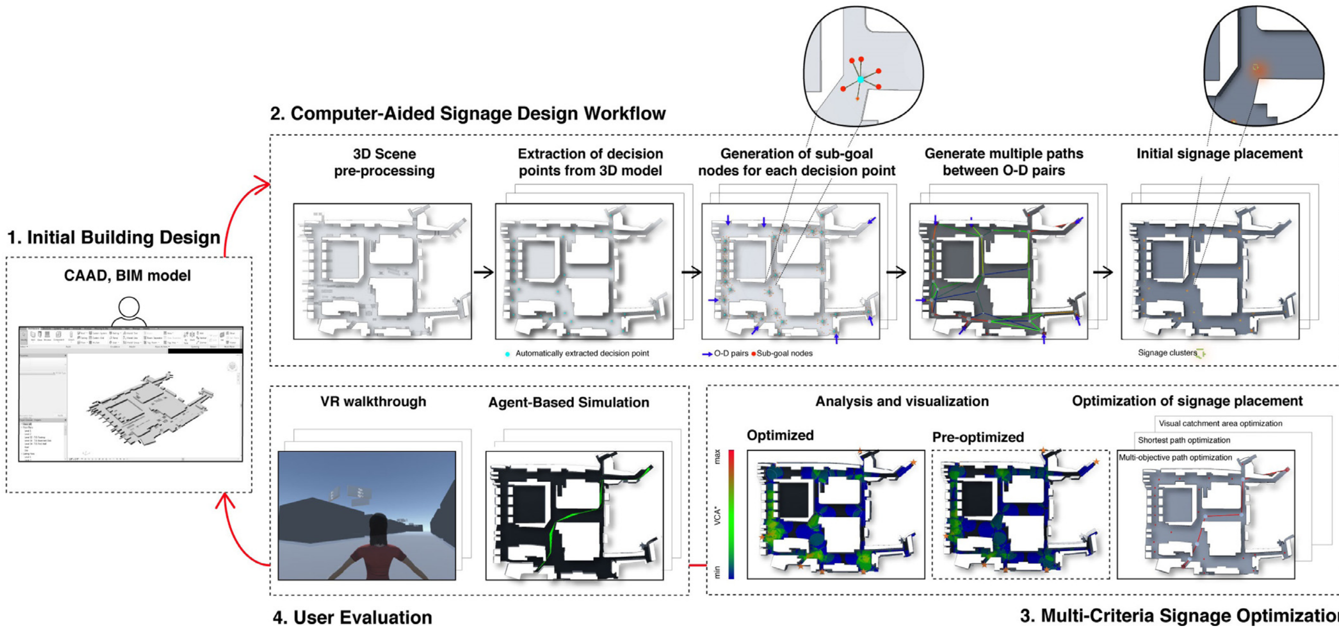



**Fig. 1.** AUTOSIGN Framework Overview. AUTOSIGN begins by taking a 3D building model, navigation tasks and user-assigned optimization parameters (Step 1), followed by an automatic pre-processing of a 3D input model, extraction of decision points, and generation of initial signage placement (Step 2). Then, multi-objective signage optimization phase produces optimized signage design based on various wayfinding cost functions to maximize the signage coverage area (Step 3). Lastly, an agent-based simulation and a VR walk-through are used to evaluate signage design from the perspective of occupants' wayfinding (Step 4).

system in the early stages of indoor navigation guidance development to improve the usability of the system. Authors in [17] proposes a biologically inspired computational model of human-signage interaction based on information theory. They conduct a crowdsourced experiment and virtual reality-based experiment to identify the role of information gain inside the visual catchment area of a sign for wayfinding decision making.

In general practice, signage placement is carefully carried out by complying building regulation and standards. For example, recommendations made in British Standard BS 5266 Part 4 provide guidelines about the format of the graphical symbol on the escape route sign, size depending upon maximum viewing distance, and photometric performance of traditional internally illuminated signs [18]. NFPA Life Safety Code Handbook [19], suggests that reflective signs with lettering height of 152 mm are legible up to a distance of 30 m. Such regulations and standards are extremely effective in designing the signage system. However, the decision as to where the signage system is placed in large complex structures is usually made when the structure is empty [20]. After the furnishing and other fittings, the signage system may become less effective or even invisible due to furnishing obstructions.

Finally, to the best of our knowledge, existing work done on automatic signage design systems in indoor built environment are limited in (a) its ability to account for the spatial complexity of signage placement (b) its ability to account for wayfinding literature to inform the optimization process.

**Comparison to State-of-the-Art-** Greenroyd et al. in [21] presented a tool that aid signage placement by using wayfinding metrics found in the literature. One limitation of their approach is the use of single wayfinding metric at a time, instead of multiple metrics, to generate a signage design. Thus, to incorporate more than one wayfinding metrics, a designer has to run the analysis multiple times. Many researchers including [22] have used visual attention patterns to aid the placement of various visual elements such as advertisement location on a website [23], and count the number of passersby to measure the exposure of advertisement panels in [24]. Though these researches motivate us to investigate the benefit of eye tracking based gaze prediction in the proposed sign location optimization step (Section 5), we leave it as an extension in future works.

Recently, Huang et al. [25] made an attempt to leverage optimization-based methods to resolve the complexity of signage design problems. In their work, they proposed automatic wayfinding optimization to generate optimized navigation paths for a large scale outdoor environment. Their method requires a designer to specify various navigation scenarios for the system to automatically generate an optimized signage design based on optimized paths. The approach uses a graph to represent the input layout, and the user/designer has to manually place nodes at intersections, entrances, and points of interests. Despite being able to overcome some of the aforementioned limitations, their method requires a designer to manually place nodes (signs) at each intersection. The agent's interaction with the sign is basic, random errors are introduced to simulate realistic wayfinding. Also, their work considered only a single path for each Origin-Destination (hereinafter referred to as O- D) pair which is not sufficient to account for the various path combinations arising from a single O-D pair. Our work aims to leverage on the motivating work in [25] and improves it by (a) automating the manual identification of decision points for sign placement (b) using a realistic agent-signage interaction model to run wayfinding simulations, and (c) optimizing signage location to improve its visibility and overall coverage area.

## 3. AUTOSIGN – a computer-Aided signage optimization framework

In this section, we present an overview of AUTOSIGN and briefly explain each component of the framework (Fig. 1).

### 3.1. Initial building design

To generate signage layout and to optimize it, AUTOSIGN requires three inputs: (1) building Geometry: the building input for AUTOSIGN can vary in the level of detail, ranging from a simplified 3D CAD model to a more detailed BIM model. At this point of the frameworks' development and to enable users to apply the

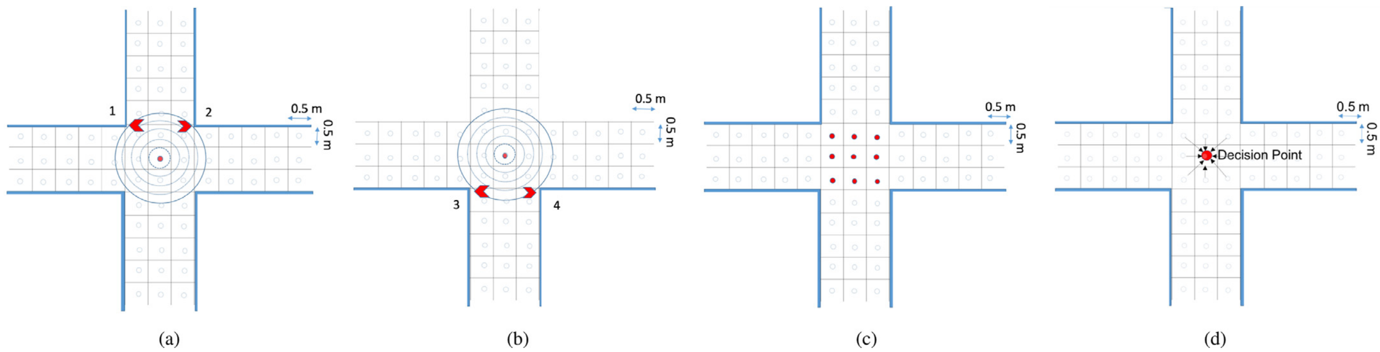



**Fig. 2.** Step by step visualization of the decision point extraction method. (a) Top down orthographic view of an intersection. The navigable surface is divided into grid cells of 0.5*0.5m. The center of each grid cell is a candidate for the decision point. One probable decision point at the center is highlighted with a red circle. Sphere-cast with 0.5 m radius is performed from the center and iteratively increased till it hits a static object(s) (i.e., point 1 and 2). (b) The hit surface(s) is(are) temporarily removed from the environment, and iterative sphere-cast continues until it hits another static object(s) (i.e., point 3 and 4). (c) All successful decision points (i.e., each having three or more sphere-cast hits) are shown. (d) The decision points close to each other are combined to represent one decision point.

proposed tool at different design stages, BIM-based semantic information linked with building geometry is not processed to inform signage generation or optimization. Instead, a geometrical approach to process a 3D building model is applied to extract the buildings' navigation graph. (2) O-D pairs: navigation tasks should be defined in the form of O-D pairs situated with respect to the building layout. (3) Optimization Parameters: designers assign weights to wayfinding cost functions based on the function of the building and design objectives, which in turn drive the signage optimization module. Given the varying level of detail in the process of signage design, AUTOSIGN is intentionally designed to operate with varying levels of information on building geometry and navigation tasks, and hence could aid designers through the different phases of signage design, from preliminary to advanced. Moreover, given that signage optimization parameters might change in the course of the design process, the user-in-the-loop function allows designers to add, eliminate or change signage optimization criteria, adapting the optimized signage design layouts generated iteratively.

## 4. Computer aided signage design work-flow

In this section, a detailed account of the computer-aided signage design work-flow (step 2 of Fig. 1) is provided. Firstly, the imported 3D map of the environment (i.e., automatically tagging wall, floor, and other static features) is pre-processed to separate the navigable areas from the non-navigable areas. This is achieved by performing a ray-cast operation from a fixed height (computed by extracting the bounds of the 3D environment) followed by a sphere-cast operation (i.e., successful contact point from a smallest sphere-cast along the ray-cast point on the floor). The navigable area is uniformly divided into grid cells of 1 $m^2$. The center of each grid cell location is registered as an input for the next stage of decision point identification.

### *4.1. Decision point extraction*

Decision points play a crucial role in the design of a signage system. Decision points are the locations at which occupants need to perform a navigational decision concerning paths and directions to select. This highlights the importance of correct decision points extraction. Aiding these decision points with directional signs are essential to implementing an efficient signage design. Carpman et al. [26] suggested that decision points should exist at more places other than intersections of paths/corridors. Decision points may include a change in the direction of a primary path, changes in environmental cues, merging of two paths, entrances and exits.

Fig. 2 illustrates the proposed decision point extraction algorithm. An increasing overlap sphere is cast from each navigation point until at least one obstacle is hit. The hit obstacle is temporarily removed from the obstacles list, and the radius of the sphere-cast is increased slightly (line 1–12 in Algorithm S1 in the supporting document) until it hits a new obstacle. Obstacle nodes that are close to one another are considered to be in the same group. If an obstacle exists between two obstacle nodes within a square encompassing the circle (checked with a raycast), the two nodes are also considered to be in the same group. A decision point is formed if three or more obstacle groups are hit. Finally, decision points that are near one another are merged to optimize the number of decision points (procedure “CleanUpDecisionPoints” in Algorithm S1 in the supporting document). To showcase the broad applicability of the proposed DP extraction approach, we test it on eight real-world indoor environments with different floorplan layouts and typologies (e.g. shopping malls, hospitals, and transit hubs). The results are presented in Fig. S2 of the supporting document. The results showcases that the proposed approach creates near-to-perfect decision points in both corridor style and non-corridor geometry. Finally, a user-in-the-loop interface is provided to enable designers to make final changes in the extracted DP by performing the move, create, and delete operations before proceeding to the next step.

### *4.2. Navigation graph: multiple path generation*

Once the decision points are extracted, a Navigation Graph (NG) $= \langle V, E \rangle$ is generated to represent the input floor layout, where $V$ is the set of extracted decision points, and $E$ is the set of straight and unobstructed navigation paths between pairs of decision points. After the designer generates points of interest (e.g., entry and exit of a building, toilets, reception desks), he or she can generate all distinct paths between each O-D pairs with a click of a button.

For each O-D pair, all decision points are used as way-points to find the least costly path (Section 5.1) from the specified origin to the specified destination via that way-point. The decision points are first sorted based on their combined distance between the origin and the destination. These paths are sorted by cost (i.e., with equal weight for all cost functions), and the least costly path is added as the first finalized path. Then, each decision point in this path is marked as used, and the algorithm will iterate through the list of decision points to find the next decision point with the shortest combined cost that is not yet used. A path is created using this next decision point as a way-point, and paths similar to any existing finalized path will be ignored. New paths are added to the list of finalized paths and the decision points used to generate these paths are also marked as used. This process continues until N number of distinct paths, as determined by AUTOSIGN users, is reached, or until the list of decision points has been completely exhausted. This process reduces the search space for the path optimization phase (Section 5).

### 4.3. Initial signage placement

Once the navigation graph is constructed, an initial signage design is generated. Firstly, signs without any directional texts are created at the termination point (i.e., start/end) of each edge of each path, with the duplicates removed. Every signboard is assigned to its parent decision point (i.e., from which it is generated). Then, the signboard assigned to each decision point is accompanied with directional information pointing towards the next decision point in the path towards the terminal. The pseudo code is provided to explain the algorithm in detail (Algorithm S2 in the supporting document).

## 5. Multi-criteria optimization formulation

In AUTOSIGN, optimization of a signage design system is a two-step process. Firstly, route choices between each O-D pair is optimized based on user-defined multi-criteria cost functions (Section 5.1) and secondly, the positions of the signboards are optimized in relation to their parent decision points for maximum local sign coverage within the bounds determined by a designer (Section 5.2).

### 5.1. Route choice based optimization

The decision points/junctions of an architectural space can be represented by an undirected navigational graph $G_N = \langle N, E\rangle$. For each O-D pair, multiple paths can exist between them. Combining all possible combinations of paths for all the pairs can make a signage design process computationally expensive and unnecessary cumbersome. To tackle this problem, AUTOSIGN relies on cognitively inspired wayfinding cost functions (described below) to reduce the possible paths between each O-D pair.

#### 5.1.1. Computation of wayfinding cost function

Human navigation (in both indoor and outdoor environments) has been widely studied in behavioural and cognitive science [27]. Many researchers in this field have highlighted the challenges in human wayfinding in an indoor environment. The challenges arise due to the complex 3D space (i.e., disorientation after vertical travel and poor cognitive map creation) [28]. Researchers have proven that during wayfinding, humans pay attention to the total path length [29,30], route complexity (i.e., number of turns) [31], and the curvature of the path [30]. Motivated by the literature [32–36] and also as proposed in [25], five crucial wayfinding cost functions are considered for the proposed optimization algorithm.

**Total path length –** Typically, occupants select the shortest path during navigation. Hence, for each path between origin and destination pair a cost, $C_{pl}$, is applied based on the length of the path. The path length is calculated based on adding the metric distance of all navigational edges between an O-D pair in the overall navigational graph (all navigational edges).

$$C_{pl} = \frac{1}{|P|L_{TE}} L(p) \tag{1}$$

where $|P|L_{TE}$ is the normalization factor with $|P|$ being the total number of O-D pairs and $L_{TE}$ is the total length of all the edges in the navigation graph. $L(p)$ is the length of the path in consideration.

**Total number of decision points –** Decision points are the location where occupants need to make a wayfinding decision about which direction to take. Paths with many decision points should be avoided as it can induce stress to the occupants and lead to error. Hence, for each path between an O-D pair, a cost function $C_{dp}$ is used to penalize the number of decision points used in each path:

$$C_{dp} = \frac{1}{|P|TDP} N_{dp}(p) \tag{2}$$

where $|P|TDP$ is the normalization factor with $|P|$ being the total number of O-D pairs and $TDP$ is the total number of decision point. $N_{dp}(p)$ is the number of decision point in the path in consideration.

**Total path angle –** According to spatial cognition [37], navigation paths with varying orientation disorients and confuses occupants during wayfinding. It can cause discomfort, and stress [38]. In the proposed framework, straight paths are preferred and a cost function $C_{pa}$ is applied to penalize the path with a larger change in the angle.

$$C_{pa} = \frac{1}{|P| * TDP * \lambda} A_{pa}(p) \tag{3}$$

where $|P| * TDP * \lambda$ is the normalization factor with $|P|$ being the total number of O-D pairs and $TDP$ is the total number of decision point and $\lambda$ is the maximum turning angle between two adjacent edges. $A_{pa}(p)$ is the sum of the absolute turning angle between the edges in the considered path.

**Global decision point degree centrality –** Paths with frequently visited decision points are encouraged by the proposed system. It is crucial in some scenarios such as shopping mall and other public gathering places to direct occupants to a common area such as ticket counter, atrium or lobby for better crowd management. The degree centrality of a decision point is calculated, and a cost function is proposed to penalize the path with less frequented decision point.

$$C_{dc} = \frac{1}{TC_{dp}} (TC_{dp} - Centrality_{dp}(p)) \tag{4}$$

where $TC_{dp}$ is the total centrality of the overall decision points and $Centrality_{dp}(p)$ is the sum of the centrality of all decision point in the considered path.

**Global edge overlap –** Similarly, to force navigational path between different O-D pairs to overlap with each other, edges which are frequented most commonly are selected in the design of preferred path between an O-D pair. A cost function $C_{eo}$ is provided which penalizes the paths with less frequented edges.

$$C_{eo} = \frac{1}{T_{oe}} (T_{oe} - T_e(p)) \tag{5}$$

where $T_{oe}$ is the total count of each edge frequented and $T_e(p)$ is the sum of the edges frequency in the considered path.

#### 5.1.2. Multi-Objective – Random Weight Genetic Algorithm (MO-RWGA)

In this section, we briefly describe Genetic Algorithm (GA) and our reasoning behind choosing MO-RWGA as the optimization approach. A multi-objective minimization problem with **K** objectives is defined as: $\mathbf{x} = x_1, x_2, \ldots, x_n$ where $\mathbf{x}$ is a n-dimensional decision variable vector in the solution space $\mathbf{X}$. We have to find a vector $\mathbf{x}^*$ that minimizes a given set of **K** objective functions given as: $z(x^*) = z_1(\mathbf{x}^*)), \ldots, z_K(\mathbf{x}^*)$.

The common approach to solve a multi-objective optimization problem is by assigning weights to each objective functions and reducing the model to a single objective problem with a scalar composite objective function as:

$$F = w_1 o_1^{'}(\mathbf{x}) + \ldots + w_k o_k^{'}(\mathbf{x}) \tag{6}$$

where $o_i^{'}(\mathbf{x})$ is the normalized objective function $o_i(\mathbf{x})$ and $\sum w_i = 1$. Solving Eq. (6) with a pre-determined weight vector $w = w_1, \ldots, w_n$ generates a single solution. To explore alternative solutions, a designer must manually vary the weight combination in a process of trial and error. This approach is tedious and time-consuming, even when the designer is highly familiar with the problem domain.

To automate the process of generating an optimal weight vector, we propose MO-RWGA, in which random weights are generated for each solution space $\mathbf{x}_i$ during the evaluation of a weighted sum of multiple objective functions at each generation. The benefit of this approach is to force multiple search directions in a single iteration without any additional parameters [39]. Wayfinding fitness function *WayfindingFitness* (line 6 in Algorithm S4 in the supporting document) used in MO-RWGA is a linear combination of five cost functions as shown in -

$$F = \sum_{k=1}^{5} W_k C_k \tag{7}$$

where $C_k$ corresponds to $C_{pl}$, $C_{dp}$, $C_{pa}$, $C_{dc}$, $C_{eo}$ and weights $W_k$ (adjusted by the designer according to the environment-specific signage design needs) are positive value satisfying

$$\sum_{k=1}^{5} W_k = 1 \tag{8}$$

Finally, we can define the proposed multi-objective optimization problem which minimizes the wayfinding fitness cost function computed above as:

$$\mathbf{O}^* = \underset{o \in \mathbb{U}}{\mathbf{argmin}}(F(\mathbf{O})) \tag{9}$$

where, $\mathbf{O}^*$ is the design vector, solution $o$ belongs to the solution space $U$ and $F(\mathbf{O})$ is computed using Eq. (7).

### 5.2. Signage coverage area based optimization

Once the optimized routes between O-D pairs (i.e., optimization step 1) are generated, AUTOSIGN optimizes the parameters of a sign (i.e., location and orientation) at each decision point to maximise the sign's local coverage area with a designer-specified bound. In AUTOSIGN, a Particle Swarm Optimization (PSO) algorithm is employed to adjust sign parameters. The strengths of the PSO algorithm are its simple implementation and rapid convergence to solve various optimization problems, which puts it on par with many global optimization algorithms such as GA and simulated annealing (SA).

#### 5.2.1. Single objective function: Sign coverage area

The objective function for fine-tuning the optimal signage location is based on its visibility catchment area (VCA). One known way of computing the sign coverage area is its VCA [2,20]. The VCA of a sign is the region where an occupant can physically receive wayfinding information from a sign. The VCA of a sign is calculated using the location of the sign, the height of the occupant, viewing angle, and the maximum distance from which the sign can be seen, which is based on the font size. Later on, in [2,40], authors simplified the VCA to an approximate circle with its radius equal to half of the viewing distance. In AUTOSIGN, designers have the flexibility to assign the value of the parameters mentioned above. Simulations are generated based on the default values of occupant height of 1.72 m, viewing angle of 120° and maximum viewing distance of 30 m. The single objective function with a set of parameters, $\mathbf{p}$, and their bounds (constraints), $\mathbb{P}$, is expressed as a maximization problem to fit the parameters as follows:

**Algorithm 1** Sign Coverage Area Cost Algorithm.

```
Input: S (Sign)
Input: P (New Position)
Input: DP (Parent Decision Point)
Input: A (Threshold Angle)
Input: G_all (All Grid)
Input: D_max (Max Sign Visibility Distance)

function Cost_covArea(S, P, A)
    Translate(S) ←random(P)
    if distance(DP, S) ≥ 0 and ⩽ DP_threshold then
        for all g_i to G_all do
            dist = distance(g_i, S)
            if dist ⩽ D_max then
                area + +
return area
```

$$\mathbf{P}^* = \underset{p \in \mathbb{P}}{\mathbf{argmax}}(f(\mathbf{P})) \tag{10}$$

where $f(\mathbf{P})$ is computed using Algorithm 1.
where $S_{ca}$ is the sign coverage area calculated using the method described in [40], P is the sign position and R is the sign rotation.

The initial sign placement (before optimization step 2) in AUTOSIGN by default is at a distance of one meter from its parent decision point, and the sign is oriented with its normal perpendicular to the previous decision point in the navigation path. The sampling of search space for a sign is bounded by a threshold distance from its parent decision point, and a threshold angle range from its original orientation. These two constraints are formulated as follows:

$$distance(S, DP) \geq 0 \text{ and } \leqslant D_{threshold} \tag{11}$$

where $D_{threshold}$ is kept as one meter to restrict the sign placement being further from its parent decision point (given the fact that the decision point is mostly extracted at the center of multiple path intersection). The user of AUTOSIGN has a flexibility to tune this value to suit the signage design needs.

$$-A_{threshold} \leqslant Angle(Sign_{new}, Sign_{old}) \leqslant +A_{threshold} \tag{12}$$

where, $A_{threshold}$ is kept low (10–20°) to restrict a substantial deviation in the new sign's relative angle from its previous decision point (i.e., the direction of occupants' approach). This is important to prevent the sign from getting oriented towards another hallway or open space for which it was not designed for. In Algorithm S3 (supporting document), we provide a pseudo-code of the PSO algorithm for finding the optimized signage location. The cost function $Cost_{covArea}$ to calculate the sign coverage area (line 7) in Algorithm S3 is described in Algorithm 1.

## 6. Optimization and experimental results

To highlight the practical use of AUTOSIGN, we begin by demonstrating the performance and time complexity in Section 6.1. We highlight the improvement in the signage coverage area by visualizing it in the form of heatmaps over two different 3D layouts (a virtual shopping mall and a virtual railway station) in Section 6.2. We then generate simulations to demonstrate the effectiveness of signage design variations before and after optimization in Section 6.3. Static images are not sufficient for an effective demonstration of a user-in-the-loop aspect of AUTOSIGN; thus we refer the reader to the accompanying video.

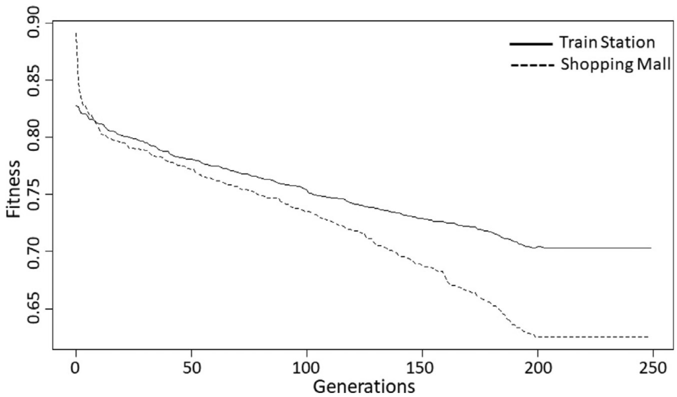



**Fig. 3.** Best Fitness values over 250 generations for multi-objective - random weight genetic algorithm.

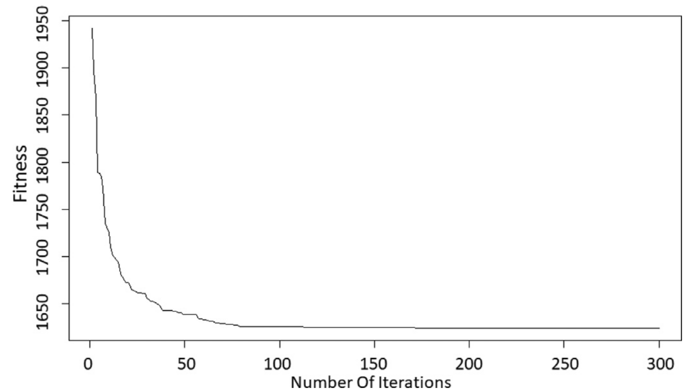



**Fig. 4.** Fitness result for one sign location optimization using particle swarm optimization.


(a) Before Optimization (b) After Optimization

**Fig. 5.** Representation of an increase in signage coverage area after PSO based sign location optimization for one example sign. Note: the subtle change in the position and orientation of the sign after optimization in (b).

### 6.1. Performance analysis

In AUTOSIGN, the navigational area of a 3D environment is divided into rectangular grid cells. It is a virtual grid map of a 2D floor plan which is used as a reference point for an agent's location. The size of a grid cell is set to 0.5*0.5 m, representing the average step length based on the average size of an adult. Average CPU time taken for generating the optimized path for all O-D pairs in the signage system using the proposed MO-RWGA along with the PSO optimization of individual sign location for two example layouts is presented in Table 3. Note that the optimization process in AUTOSIGN is a two-step process with MO-RWGA executed first, followed by the PSO optimization. Average CPU time taken for generating the optimized path for all O-D pairs in the signage system using the proposed MO-RWGA along with the PSO optimization of individual sign location is reported for two example layouts in Table 3.

#### 6.1.1. MO-RWGA optimization

Fig. 3 shows that MO-RWGA reaches the optimal point after 250 iterations. De Jong et al. [41] recommended a crossover rate between 0.65 and 1, and mutation rate between 0.001 and 0.01 in GA applications. In AUTOSIGN, the crossover probability level is set as 0.8, and the mutation level is 0.05, where 0.05 is equal to 1/n, and population size n is set to 20. We achieve the best performance with the above parameters over 250 iterations for both layouts. Total time of 63.5 and 161.84 s was observed for the shopping mall and railway station respectively. Higher computation time in the case of the railway station was due to the higher number of O-D pairs.

#### 6.1.2. Particle swarm optimization

Fig. 4 shows that PSO reaches the optimal point after 300 iterations. We achieve the best performance with 20 particles in the swarm and 300 iterations. The average time of 3.96 s and 3.73 s per sign was observed in the virtual shopping mall and the virtual railway station respectively, as shown in Table 3. The efficency of PSO can be further improved by precomputing sign visibility value per grid.

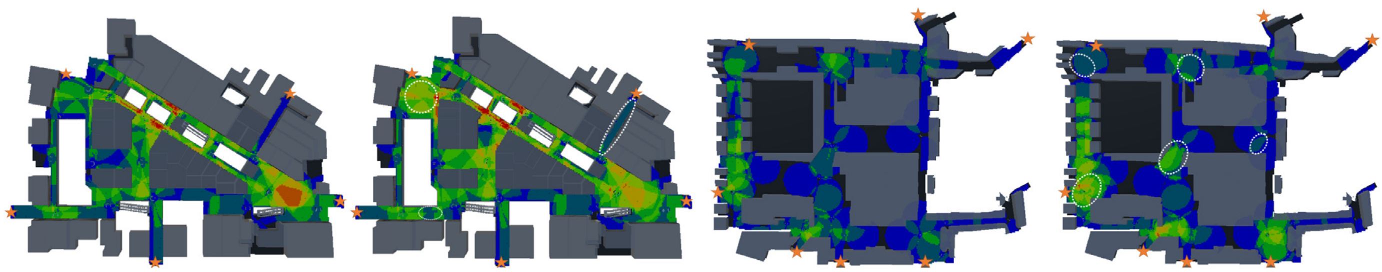
### 6.2. Signage coverage area

Table 3 highlights the gain in signage coverage area after performing PSO-based sign location optimization for all signs. We observe an increase of 16.22% and 19.06% in the sign coverage area for the virtual shopping mall and the virtual railway station, respectively. In Fig. 5, we demonstrate a micro view of sign coverage area gain for one example sign. We observe that the initial placement of the sign was behind a wall and was not visible for an occupant from the narrow corridor in between two walls. The sign's visibility was restricted to close proximity. After optimizing its location, we notice an improvement in visibility and its coverage area as shown in Fig. 5(b). This increase in signage coverage area can help in reducing the wayfinding error during navigation. In Fig. 6, we showcase the overall gain in signage coverage for the signage system in two different scenarios post-optimization. The O-D pairs in both layouts are represented with an orange star.

### 6.3. Agent-based simulation to assess wayfinding performance across signage layouts

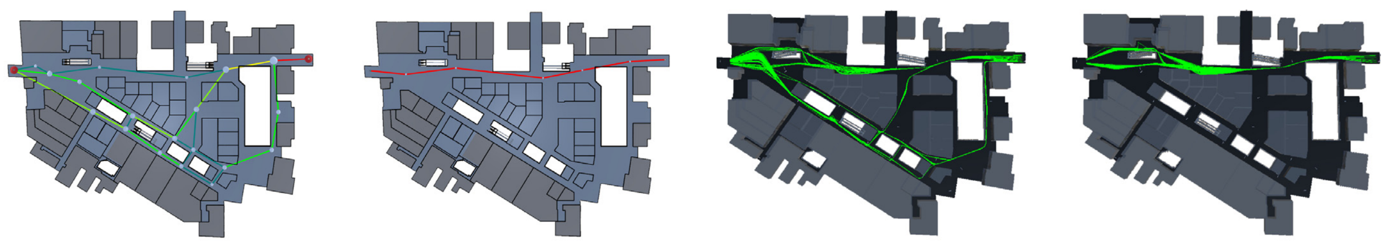
Here, we present the result of generating wayfinding designs under different signage design options for two very different layouts – a virtual shopping mall and a virtual railway station. In Fig. 7, we show the signage design generated before optimization (maximal: best three possible paths from O to D), and after optimization (minimal: Best path based on cost functions). To highlight the changes in the occupants' navigation behaviour for different signage designs, we employ an agent-based simulation as described below. We perform a wayfinding task for one randomly selected O-D pair. We simulate 100 agents in each of the two conditions and produce various wayfinding measures. We report our findings in Table 1.

We employ a simple version of the agent-signage interaction based wayfinding system that is inspired by vision-based wayfinding simulation using a cognitive agent-signage interaction model as described in [17]. In the proposed context, a signage system consists of a set of signs $S_i$. Individual sign comprises of its



(a) Shopping Mall: Before (b) Shopping Mall: After (c) Railway Station: Optimization (d) Railway Station: Optimization

**Fig. 6.** A heatmap visualisation of an increase in signage coverage area after performing particle swarm optimization. We notice an increase in signage coverage certain areas highlighted using dashed ellipses in (b) and (d). The areas shown in red are influenced by more number of signs and the areas shown in blue means they are influenced by less number of signs. The area shown in black has no signage coverage. The orange star symbol represents the origin and destination. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(a) Multiple path route before optimization (b) Most optimized shorted path after optimization (c) Agent trajectories before optimization (d) Agent trajectories after optimization

**Fig. 7.** (left) Navigational paths between origin and destination before and after path navigation optimization for virtual shopping mall. (right) Visualization of the simulated agent trajectories before and after signage layout optimization for the same.

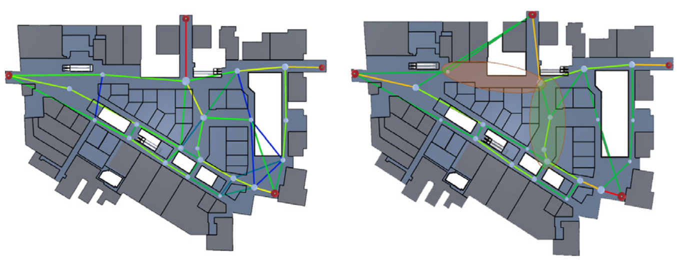


**Fig. 8.** Effect of varying the weights of edge overlap cost function on the edge connectivity of a navigation graph. By varying the weights of edge overlap cost function in the visualized navigation graph (a), an edge is removed (highlighted in orange ellipse as shown in (b)) and the connectivity is re-routed through a more centralized edge as highlighted in green ellipse. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 1**
Various performance measures before and after signage design optimization for two 3D virtual layouts.

| Environments | Conditions | Average Distance | Average Time | #Signs | Success Rate |
|---|---|---|---|---|---|
| Shopping Mall | Before Optimization | 185.4 | 219 | 23 | 100% |
| | After Optimization | 144.1 | 213 | 6 | 100% |
| Railway Station | Before Optimization | 311.8 | 122 | 12 | 100% |
| | After Optimization | 295.2 | 108 | 5 | 100% |

legibility attributes along with the list of goal locations ($A_i$, $G_i$). Two physiological aspects of an occupant are embedded in the agent framework: occupants' eyesight and height. In AUTOSIGN, occupants' eyesight is considered as near perfect with no defect Average eye height of 1.72m is considered for running the simulation. The user in AUTOSIGN can refine these parameters based on the population distribution of a building.

An agent's interaction with a sign can be broken down into a series of phases such as searching for a sign, detecting a sign, approaching a sign, perceiving the information written on a sign, and finally acting on the decision made. In AUTOSIGN, a sign is visible when an agent is inside the sign's VCA and can see the sign without occlusion. 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. If a sign is detected with the destination information, the agent proceeds towards the direction provided. In the absence of a sign or a failure to detect a sign, the agent randomly decides on the direction of one of the sub-nodes of that specific decision point with equal probability.

For each O-D pair, $N$ number of user-specified agents are spawned and assigned a task of walking from origin to destination. An AUTOSIGN user can assign different values of $N$ to simulate the signage design under different crowd densities. An agent's walking trajectory, distance walked, number of signs used, and success/failure in reaching a goal are recorded. An agent successfully reaches a sign when the distance travelled to the destination is less than 1.5 times [25] the baseline distance (shortest optimal path without any mistake). In all other cases, a failure is recorded for that wayfinding trial. Simulation results were generated by assigning agent's walking speed to 1.5 m/s. We simulate $N = 100$ agents in each of the two conditions and produce various wayfinding measures. We report our findings in Table 1.

### 6.3.1. Virtual shopping mall

We use the layout of a real-world shopping mall as an input to design a simple 3D virtual shopping mall. The O-D pairs were carefully chosen as a reflection of actual crowd flow. For the purpose of simulation, one O-D pair was randomly selected out of five and marked with a red circle as shown in Fig. 7(a). Fig. 7(a) and (b) show the possible navigation paths from O to D before and after optimization respectively. The respective agent trajectories are visualized in Fig. 7(c) and (d). The average distance travelled and the average time taken by an agent to go from O to D before optimization is relatively higher as shown in Table 1. More importantly, the number of signs required after optimization was significantly

**Table 2**
Quantitative analysis of signage design variation by changing the weights of cost function on the average distance and time taken by 100 agents for a virtual shopping mall (Fig. 8). PL (Total Path Distance), DP (Total Number of Decision Point), PA (Total Path Angle), DC (Degree Centrality), EO (Edge Overlap). Lower weights signifies higher preference as the optimization function minimizing the total fitness cost.

| Cost Function Weights | | | | | Avg. Distance (m) | Avg. Time (s) |
|---|---|---|---|---|---|---|
| PL | DP | PA | DC | EO | | |
| **0.111** | 0.222 | 0.222 | 0.222 | 0.222 | 151.2 | 208 |
| 0.222 | **0.111** | 0.222 | 0.222 | 0.222 | 162.4 | 211 |
| 0.222 | 0.222 | **0.111** | 0.222 | 0.222 | 153.8 | 208 |
| 0.222 | 0.222 | 0.222 | **0.111** | 0.111 | 185.8 | 219 |
| 0.222 | 0.222 | 0.222 | 0.222 | **0.111** | 173.2 | 214 |

lower. This reduction in the number of signs reduces the clutter of information and minimizes the cost of signage design. The success rate of reaching the destination was 100% in both pre- and post-optimization. Similarly, we performed signage design variation for a virtual railway station (Section 1 in the supporting document).

### 6.3.2. Variation in signage design

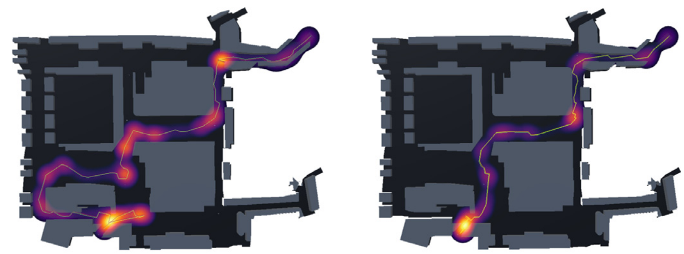
In this section, we quantitatively and qualitatively evaluate the signage-design variations by systematically adjusting the relative influence of the proposed cost functions. In Table 2 we perform a quantitative analysis by systematically changing the weights of various cost functions and its impacts on the average distance traversed and time taken by simulating 100 agents as described earlier in Section 6.3. We notice that the average distance travelled and time taken is lowest when higher preference is assigned to the weights of *Total Path Length*, and *Total Path Angle* cost functions. This is because both cost functions focus on minimizing the distance and prefer straight path involves fewer turns. In Fig. 8, we visualize the change in navigation graph by giving higher preference to *Total Edge Overlap* (i.e., the weight is halved as shown in the last row of the Table 2) Specifically, we notice that the navigation edge between two decision points is missing in the area marked with a semi-transparent orange ellipse (Fig. 8(b)) which was earlier present (Fig. 8(a)). The path has been re-routed using the edges marked with a green semi-transparent ellipse. This may be important if the designer of the building wants people to navigate via a particular area of commercial/safety interests.

## 7. User evaluation

AUTOSIGN was evaluated for two criteria: (1) system usability from the perspective of a typical designer user. (2) Wayfinding performance across optimized and non-optimized signage layouts from the perspective of a novice occupant. To evaluate the design and usability of AUTOSIGN (i.e. criterion 1), we conducted a System Usability Test. To evaluate occupants' expected wayfinding performance (i.e. criterion 2) an expert-based VR walk-through was carried out.

### 7.1. System usability test

To evaluate the design and usability of AUTOSIGN, we conducted a System Usability Test (SUS) [42]. Four experts (two female and two male, age 34.25 ± 2.96 years) were recruited to participate in the usability study. None of them had previous exposure to AUTOSIGN. They received a general introduction to AUTOSIGN and a brief explanation of the user interface. Experts were asked to use the system and design a signage system for a virtual 3D shopping mall and a 3D railway station for *N* terminals (source and destination). In addition, they were told to design the signage



(a) Pre-optimized signage layout (b) Post-optimized signage layout

**Fig. 9.** Heatmap analysis of experts stay-duration along path points in VR.

system with respect to the shortest path between each terminal pairs. After completing the signage design, experts were asked to evaluate AUTOSIGN's user interface by completing an online SUS survey. The average SUS score obtained was 63.75 ± 4.84, indicating a slightly below average (i.e., average SUS score is 68) SUS level of usability and product acceptance. The values for adjective rating from the experts were "good", "good", "excellent" and "good" which when converted to SUS score results in 74.925 (i.e., Grade B+ and Good) according to Bangor et al. [42]. This preliminary study conducted with a small number of experts indicates the value of this tool in its ability to aid designers in the signage design process. This is evident in the reasonable usability scores and the qualitative feedback given by the subjects as described below. The SUS is slightly below the average. This can be attributed to the low number of users and proof-of-concept nature of the user interface. For future work, we will polish and refine the interface and conduct a large scale study for a more definitive evaluation of the tool. The comments received from the experts were encouraging, and we list them below:

- Participant 1: 'The tool is very useful and the layout generated is not trivial. I would like to use it for additional design purposes.'
- Participant 2:'The process is simple and results are powerful. Still, I would prefer to use the tool inside a modeling software.'
- Participant 3: 'A great tool!.'
- Participant 4: 'Would be great to access the 3D model after the signage generation and adapt the model.'

### 7.2. Expert-based VR walk-through to assess wayfinding across signage layouts

Once participants completed the first step of signage design they were asked to perform a walk-through from the perspective of a novice occupant. They repeated the walk-through again after optimizing the signage layout. The 'first-person' walk-through feature that was built-in to the AUTOSIGN interface was used to support this evaluation step. This type of expert evaluation aims to leverage experts' experience and cognition and provide an immediate evaluation of the generated signage with regards to wayfinding. Such feedback could prove especially useful in the context of the architectural design process where complex experimental procedures are challenging to apply. A sample trajectory of one of the experts chosen is showcased in Fig. 9. This expert was an architect with a high degree of familiarity with the layout of the railway station. Fig. 9 shows the same navigation task (i.e. same O-D pair) performed by the same expert across both optimized and non-optimized layout. The following wayfinding performance measures were recorded; (1) distance covered (2) time to reach the destination (3) stay-duration at decision points and (4) trajectory. Results showcase analysis of a single expert who performed the same task. The task was performed across both non-optimized and optimized signage layouts for the case of the railway station. With

**Table 3**
These results were computed on a standard computer Intel(R) Core(TM) i7-6700K with 4.00 GHz processor and 16 GB RAM for two different environments. Note that while the system is not real-time, it is sufficiently fast to support the use of a user-in-the-loop.

| Environments | #O-D pairs | #Signs | Area Before Optimization ($m^2$) | Area After Optimization ($m^2$) | Total GA Time (s) | PSO Avg. Time (s) |
|---|---|---|---|---|---|---|
| Shopping Mall | 10 | 67 | 38,740 | 45,025 | 63.5 | 3.96 |
| Railway Station | 14 | 70 | 55,206 | 65,730 | 161.84 | 3.73 |

**Table 4**
Expert walk-through performance before and after signage design optimization for the virtual railway station.

| Signage | Environment | Task O-D | Distance (m) | Time (s) |
|---|---|---|---|---|
| Non- Optimized | Zurich Train Station | A-B | 546 | 364 |
| Optimized | Zurich Train Station | A-B | 349 | 233 |

regards to the distance covered, the length of paths differs substantially between the two layouts. As can be seen in Table 4, in the optimized layout, the length of experts path was 349 m whereas, in the pre-optimized layout, it was 546 m. This difference could be related to the shortest-path optimization step used to position signs in a way that directed occupants along the shortest path for the selected O-D pair. Similarly, the time taken to reach the destination was longer in the pre-optimized layout than in the optimized one. A more in-depth understanding of the time dimension is visualized in Fig. 9 showcasing a heatmap analysis of stay-duration along with path points. Experts' stay duration along path points in the pre-optimized layout is longer than in the optimized layout. This variance in stay-duration could indicate difficulty to make a wayfinding decision on the basis of signage information along with specific path points (i.e., decision points and intersections). This explanation, however, is inconclusive. Alternative methods to gain qualitative feedback (e.g. think-aloud protocols) could have been applied to provide a richer explanation of observed behavior. Yet, this approach would have hindered the possibility of comparing agents' performance to that of experts. Recorded trajectories from the expert walk-through under both layouts are very similar to agents' trajectories for the respective layouts after optimization, as shown in Figure S1 (d) in the supporting document and Fig. 9.

## 8. Conclusion and future works

We have presented a multi-objective two-step optimization approach to a complex signage design problem. As demonstrated, the use of AUTOSIGN has proven useful to aid wayfinding in a manner that aligns with designers' optimization criteria (i.e., reducing overall walking distance, optimizing the number of signs, thus reducing cost of installing signs and overall walking duration).

The proposed optimization-based signage design tool provides designers with the computational power to quickly visualize the interplay of different O-D pairs. The automatic placement of directional texture on the signs and the VR walk-through supports the user-in-the-loop aspect of AUTOSIGN and allows for informed design iterations. AUTOSIGN can be applied during various design stages of building design (from preliminary design stages to retrofit) to reevaluate the efficiency of an existing signage system which may get occluded due to refurbishment (e.g., an advertisement for retails in an airport terminal or due to special offers boards in a supermarket). In addition to its current application of signage positioning, the tool functionalities can be further used to optimize the positioning of additional building elements to support wayfinding (e.g., beacons and maps) based on various criteria. Compared to traditional, often manual and intuition-based approaches the proposed AUTOSIGN framework provides a complementary computational approach that supports quick and customized signage layout generation informed by a built-in usability evaluation of each generated layout.

**Future work.** We plan to integrate a cognitive agent-based simulation for wayfinding to validate and optimize the design of signage systems from the perspective of varied occupant groups. By integrating a cognitive agent simulation to evaluate each automatically generated signage design, we aim to leverage the use of simulation to support human-centric optimisation of building systems. We are also motivated to adapt AUTOSIGN to support signage generation and optimization in more complex building environments, namely multi-level buildings. To enhance the generative process of signage layouts with semantic information, advanced IFC processing of BIM to inform signage optimization will also be considered. Finally, we aim to extend the proposed navigation graph representation of the complex environment to hierarchical navigation graph representation to incorporate different hierarchies in the design of the signage system.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## CRediT authorship contribution statement

**Rohit K. Dubey:** Conceptualization, Methodology, Software, Writing - original draft, Visualization. **Wei Ping Khoo:** Software. **Michal Gath Morad:** Visualization, Writing - review & editing. **Christoph Hölscher:** Supervision. **Mubbasir Kapadia:** Supervision, Writing - review & editing.

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## Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cag.2020.02.007

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