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A study of pedestrian wayfinding behavior based on desktop VR considering both spatial knowledge and visual information

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A R T I C L E I N F O

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A B S T R A C T

Understanding pedestrian wayfinding behavior is crucial for traffic management and building design. The use of virtual reality technology presents an efficient approach for investigating pedestrian wayfinding behavior in large public spaces, offering numerous advantages for data collection. However, the impact of different scenario dimensions on pedestrian wayfinding behavior in large public spaces remains unclear. Additionally, the selection of virtual experiment scenario dimensions currently relies primarily on researchers' experience and practical conditions, lacking sufficient evidence to support their rational. Another challenge is the limited focus on spatial knowledge's effect on wayfinding behavior, with insufficient analysis of the utility of pedestrian visual information and a lack of precise methods to quantify visual field information accurately. This study addresses these gaps by incorporating spatial knowledge at multiple scales and pedestrian visual field information as influencing factors in the analysis of wayfinding behavior. Furthermore, it distinguishes between three-dimensional and two-dimensional scenarios to compare the impact of dimensional differences on pedestrian wayfinding behavior. By analyzing behavior data from non-immersive wayfinding experiments, this research employs statistical analysis methods and a deep learning framework to derive results regarding the factors influencing wayfinding behavior. The findings demonstrate that considering both spatial and visual field information effectively enhances the predictive ability of the wayfinding model. Additionally, dimensional differences significantly influence the pedestrian wayfinding process. These results offer empirical evidence to guide researchers in selecting experimental scenarios of pedestrian behavior and provide insights for public space layout, signage design, and improving pedestrian efficiency.

1. Introduction

The study of pedestrian dynamics is essential in large public spaces, including transportation stations and event venues, where a large number of pedestrians move with a high degree of freedom. Understanding the decision-making process of pedestrians as they navigate from one position to another is crucial for studying pedestrian dynamics. By studying the choices pedestrians make when selecting their routes, it becomes possible to identify the distribution of pedestrians along feasible paths (Adrian et al., 2019), allowing for accurate predictions of pedestrian density, flow, and crowd dynamics within infrastructure. Currently, the understanding of the

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wayfinding mechanism in pedestrian behavior suggests that pedestrians either plan their routes in advance based on global knowledge (Tong and Bode, 2022) and follow them from start to finish or, in cases where their awareness of the environment is limited, such as when vision is obstructed, they make decisions based on local spatial information (Tong and Bode, 2021). Currently, there are two types of indoor navigation modalities that facilitates pedestrian wayfinding, including 2D and 3D. However, it is unclear whether the use of different navigation modalities makes a difference in pedestrian route choice in space. Thus it is important to understand the mechanism of wayfinding under the two modalities. Meanwhile, we consider the influence of spatial information, visual field information and signage information in public spaces. On this basis, we compare and analyze the differences in path selection behaviors of pedestrians in 3D and 2D perspectives, and quantify the contribution of the above spatial and visual factors to pedestrian selection in different dimensions. The findings from this research will provide insights for the design of building layouts, infrastructure, and signage in practical settings.

Pedestrian wayfinding behavior is influenced by a combination of limited environmental information and the heterogeneity of pedestrians themselves (Haghani and Sarvi, 2018). Previous research has identified various factors that impact pedestrian route choices, which can be categorized into three components: personal, environmental, and disturbance factors (Wang et al., 2021a). Personal factors include familiarity with the environment, age, gender, neighborhood behavior, social interactions, and the desire to maintain group cohesion with friends or family (Sadri et al., 2014; Dulebenets et al., 2019; Kinateder et al., 2018; Haghani and Sarvi, 2017; Kinateder et al., 2014). Environmental factors include route length, obstacles, directness of the route (Basu and Sevtsuk, 2022; Vallis and McFadyen, 2005; Gabbana et al., 2021; Srinivasan et al., 2017; He et al., 2023). In addition to analyzing environmental factors related to spatial knowledge, sensory-based factors such as signage information and visual field information have been shown to impact pedestrian decision-making during wayfinding (Yu et al., 2023; Li et al., 2021, 2019; Zhou et al., 2021; Liu and Neisch, 2023). Furthermore, studies have demonstrated that disturbance factors like smoke and ventilation conditions in the environment (Gao et al., 2022; Zhang et al., 2021) also influence pedestrian movement decisions to some extent.

Two main approaches for studying pedestrian wayfinding behavior are field observation and controlled experiments. Early research relied on field observations of pedestrians (Asano et al., 2010; Muraleetharan et al., 2005; Hölscher et al., 2006; Barati et al., 2021; Nilsson and Johansson, 2009; Haghani and Sarvi, 2016) to understand and predict the factors influencing pedestrians' decisions by analyzing individual wayfinding methods. While field observations realistically capture pedestrian activity, they lack control over external factors such as smoke, lighting, and the presence of other pedestrians. Additionally, field observations do not directly capture information like the pedestrian's visual field or observations of signage. On the other hand, controlled experiments address these limitations but come with drawbacks related to experimental control, cost factors, and result accuracy, which can restrict the study of pedestrian behavioral influences using this method. The emergence of VR has provided a novel solution to overcome the challenges associated with traditional pedestrian data collection methods. VR technology allows researchers to construct virtual scenarios that simulate real spaces, enabling the investigation of pedestrian wayfinding behavior in controlled environments. This approach has gained popularity due to its ability to address the limitations of traditional methods. VR-based experiments in the study of pedestrian behavior can be categorized into two-dimensional scenario experiments (Li et al., 2019; Tong and Bode, 2022; Furukawa, 2015; Dong et al., 2021) and three-dimensional scene experiments (Dong et al., 2022; Kwee-Meier et al., 2019; Dubey et al., 2019; Feng et al., 2022a). These experiments can also be classified based on the type of device used, such as head-mounted displays and desktop VR, resulting in immersive experiments (Vilar et al., 2014; Feng et al., 2021; Cosma et al., 2016; Cao et al., 2019) and non-immersive experiments (Bode et al., 2014; Silva et al., 2013; Moussaïd et al., 2016). Existing research has demonstrated the effectiveness of VR in studying pedestrian behavior across various contexts. Compared to field observation experiments, VR-based experiments offer advantages such as reduced experimental time, lower costs in terms of economics and labor, and higher data accuracy. When comparing immersive and non-immersive virtual experimentation methods, studies have indicated that the differences in experimental equipment do not significantly affect pedestrian behavior, thus validating the use of both methods (Feng et al., 2022b). However, an unresolved issue pertains to whether different scenario views, specifically three-dimensional and two-dimensional views, result in differences in pedestrian wayfinding behavior. The amount and type of information pedestrians gather within the scene vary between these views, potentially leading to variations in their behavior within the virtual environment.

This paper aims to contribute by examining the impact of using different dimensions of VR scenarios (i.e., 3D and 2D) on pedestrian behavior firstly, focusing on differences in pedestrian wayfinding behavior.

The second research aim of this paper is to analyze pedestrian wayfinding behavior by considering four factors: route length, spatial knowledge of the relative location of the starting point and destination, signage information, and pedestrian visual field information. These factors are chosen for the following reasons. Firstly, distance and signage are commonly available spatial information in real-world scenarios and can be easily measured and quantified. Analyzing their utility can provide insights that can be applied to other spatial contexts beyond the specific study scenario. Secondly, virtual experiments offer the advantage of accessing first-person pedestrian visual field data effectively. Therefore, we include pedestrian visual field information in the analysis of pedestrian wayfinding behavior. Lastly, previous research has indicated that both spatial knowledge and pedestrian visual field have an influence on pedestrian route selection (Dong et al., 2022). However, what is currently lacking is specific quantitative results on the impact of these factors on the pedestrian wayfinding process and validation within a virtual environment.

Based on previous research, we predict the following effects of the investigated factors on pedestrian wayfinding behavior. Generally, pedestrians tend to prefer routes that they expect to complete in the shortest time or that have the shortest distance (Kemloh Wagoum et al., 2012). Therefore, in this study, pedestrians are likely to choose shorter distance routes to their destination. Similarly, pedestrians have a tendency to approach their destinations quickly, which may lead them to select routes that result in lower distance offsets from their destinations (Chan et al., 2022). Regarding signage information, previous research has demonstrated that differences in sign size, symbol combinations, and visibility can significantly impact the average evacuation speed of a crowd during emergency situations (Jeon et al., 2019; Li et al., 2021; Wong and Lo, 2007). Furthermore, as the number of decisions made during a pedestrian walk increases, individuals tend to become less sensitive to information (Tong and Bode, 2021). Based on this research, it is hypothesized that pedestrians will exhibit a preference for specific types of signage and that the effectiveness of signage on pedestrian wayfinding will decrease as the experiment progresses. Research on visual field information has been limited to pedestrians' self-descriptions of their vision or geometric approximations of the visual field to calculate spatial information within it (Zhou et al., 2021; Liu and Neisch, 2023). The results of the current study (Li et al., 2019) suggest that, all other environmental factors being equal, pedestrians are more likely to choose wider routes to walk. Based on this, the study anticipates that individuals will select paths that occupy a larger proportion of their field of view.

The main contributions and innovations of this study are summarized below:

(1) By utilizing VR technology, a virtual scenario is created to accurately replicate a real large public space. This virtual experiment is conducted to examine the impact of pedestrian wayfinding behavior under two different dimensions, while eliminating the influence of disturbance factors.

(2) The study takes into account the influence of four factors: route distance, position offset, signage information, and visual field, which encompass spatial knowledge and visual field information. This comprehensive analysis enhances the predictive capability of the pedestrian route choice model, thereby improving the understanding of pedestrian wayfinding behavior.

(3) In terms of technical advancements, a deep learning-based semantic segmentation method is proposed to accurately quantify pedestrian visual field information. This involves extracting multi objects within the pedestrian's visual field and classifying them to calculate their proportion. Additionally, information entropy theory is applied to quantify the information conveyed by sign sequences along the route. The findings demonstrate that as the pedestrian decision-making process progresses, there is a decrease in sensitivity to information.

The structure of the remaining sections of the paper is outlined as follows:

In section2, we provide a detailed description of the VR experiment platform used and explain the methodology employed in conducting the virtual experiment. We also outline the data collection process utilized in the study. In Section 3, we present the results of the analysis conducted for each of the influencing factors. The findings and insights derived from the analysis of factors such as path distance, position offset, signage information, and visual field are presented and discussed. Section 4 focuses on the analysis and comparison of wayfinding models across different scales and dimensions. We examine the performance and effectiveness of the models in predicting pedestrian behavior and explore any variations observed in the models based on the different experimental conditions. In Section 5, we delve into a thorough discussion of the findings obtained from the study. We analyze the implications and significance of the results in relation to pedestrian wayfinding behavior and discuss their potential applications in real-world scenarios. Finally, in Section 6, we draw conclusions based on the overall results and discussions presented in the previous sections. And offer insights for future research directions in the field of pedestrian wayfinding behavior.

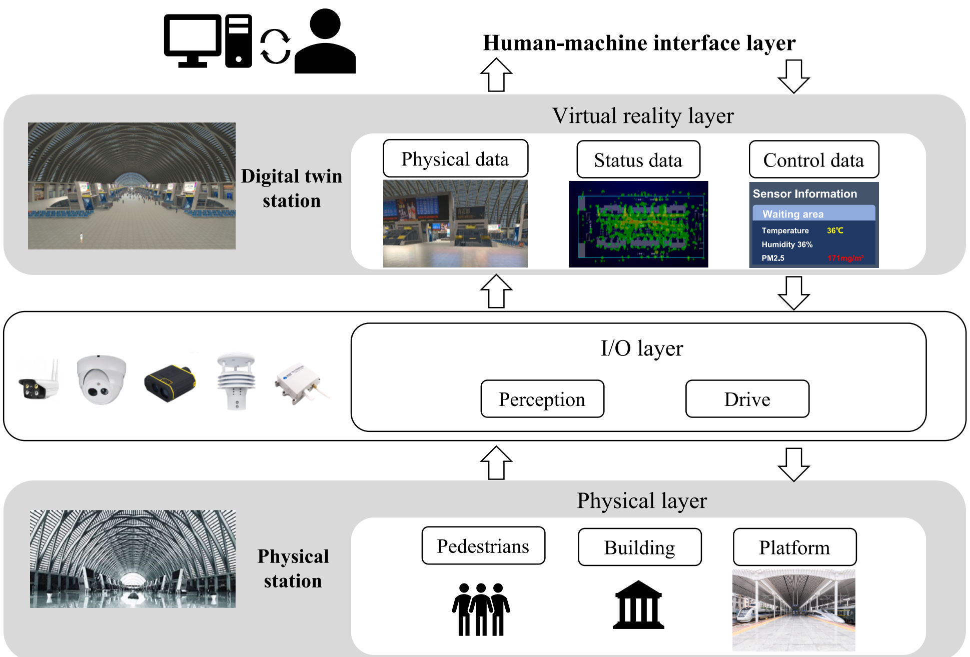

Fig. 1. VR experiment platform based on actual transportation scenario spatial data.

2. Methods

Established research has demonstrated the effectiveness of VR for conducting pedestrian behavioral experiments (Dong et al., 2022), and related research has further validated the equivalence of desktop-based VR and immersive experiment (Feng et al., 2022b). Therefore, our research is conducted as a controlled experiment in the non-immersive format based on the construction of a VR scenario of large public space. A controlled experiment means that given a starting point, pedestrians are allowed to move through a specific environment and reach a defined destination, the advantage of this method is the elimination of possible interfering factors in the real environment, resulting in experimental reproducibility and accuracy of results. This section provides a detailed explanation of the experiment methodology, including experiment scenario design, experiment task design, experiment procedure and data collection.

2.1. Experiment scenario design

The virtual reality platform utilized in our study is developed using a transportation hub as the source of actual data. This allows us to investigate pedestrian wayfinding behavior in a realistic large public space with various facilities, equipment layouts, and signage. The virtual reality platform used in our study is illustrated in Fig. 1. The VR platform includes several immersive virtual transportation scenarios where participants can navigate and interact as passengers. Using this VR platform, researchers can manipulate variables such as facility layouts and pedestrian signage to study factors influencing pedestrian behavior, such as decision-making and response to travel information. The VR platform comprises four main components: the physical layer, the I/O layer, the VR layer and the human–machine interface layer. In the physical layer and I/O layer, sensors and devices collect data on pedestrians and spatial information from the actual public space, which is then transmitted to the VR layer. By utilizing the acquired physical space data, state data, and control data, the VR scene is accurately mapped to the real public space. For the human–machine interface layer, 3D models are created to implement the human–computer interaction functionalities. Since the study setting is pedestrian wayfinding behavior under normal conditions and temporal factors (travel time and speed) are not considered in this study, the walking speed of the pedestrians is set to 1.7 m/s to make the experiment more efficient, with a 110-degree field of view (Feng et al., 2022b). Moreover, the configuration provides participants with the ability to move freely in a 360-degree range along the horizontal plane, along with panoramic views spanning both the horizontal and vertical dimensions.

Figs. 2 and 3 provide a comprehensive representation of the virtual environment used in our study. Fig. 2 shows a top view of the environment, presenting the layout and spatial arrangement of various components. Fig. 3 depicts the floor plan, illustrating the dimensions and distribution of different areas within the scenario. The virtual environment consists of several distinct regions. Entrance area is highlighted in yellow, serving as the starting point for participants. Obstacles are represented by dark grey areas and white grids, creating barriers that pedestrians must navigate around. The target area, where participants aim to reach, is marked in red. Within the scenario, there are two steps where pedestrians are required to make route choices. The first step, denoted as Area A (light blue area in Fig. 3), presents participants with six possible routes to cross from the yellow area to the central white area. The routes are labeled as 1 to 6, starting from the top and progressing downward in Fig. 3. Once participants have successfully crossed to the white area, they encounter the second route selection point, referred to as Area B (also indicated by a light blue area in Fig. 3). At this point, participants must independently choose a new route to traverse through the obstacles and ultimately reach their destination in the red

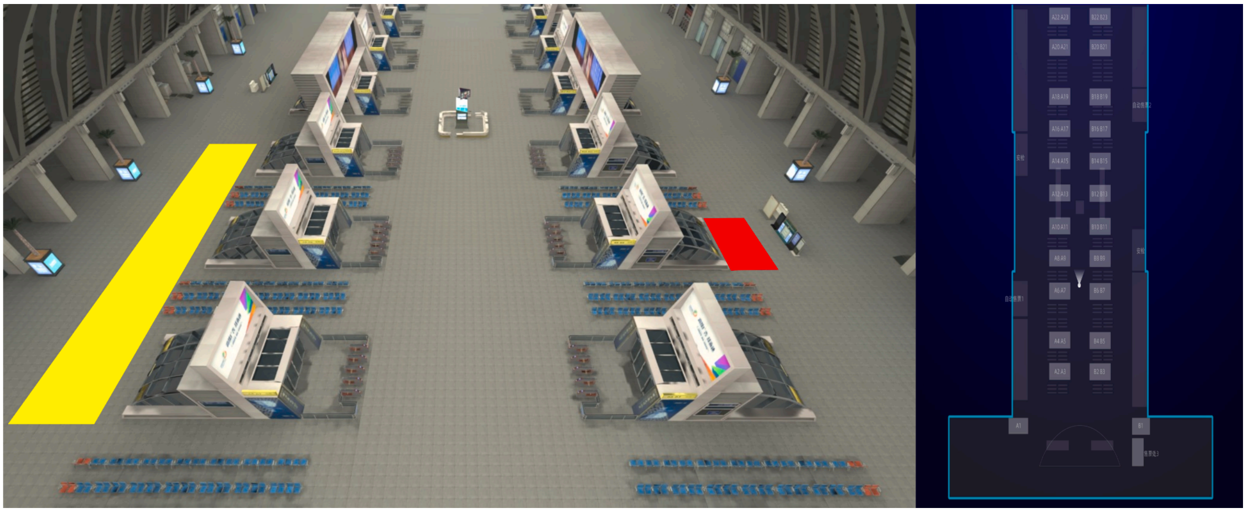

Fig. 2. Comparison of experimental scene presentation in pedestrian vision under different dimensional conditions (3D: left, 2D: right). In the left, the yellow area is the initial area of pedestrian departure, and the red area is the destination. All obstacle components in the setting scene in the experiment cannot pass through. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

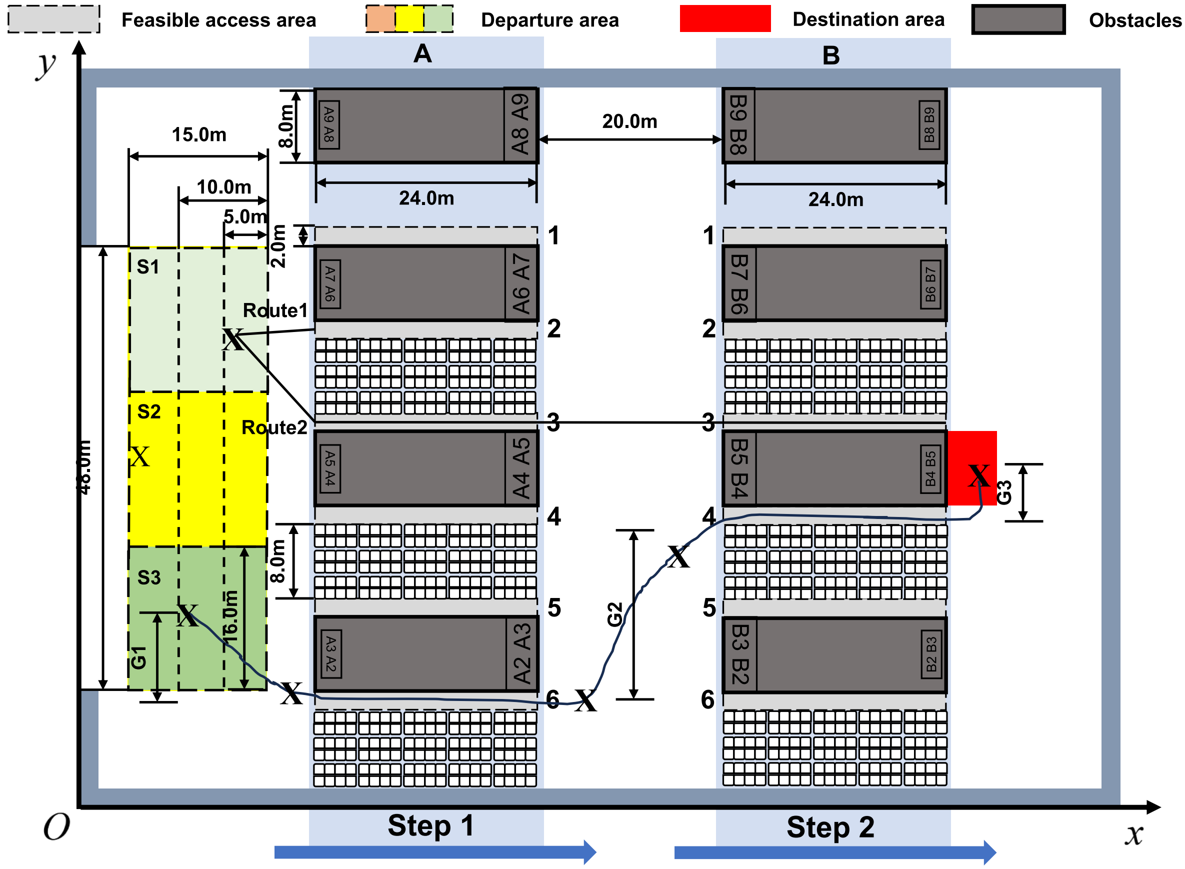

Fig. 3. The plane layout of the virtual experiment scenario in this study. The yellow area is divided into three groups of experiments: S1 to S3 and in each area participants need to complete corresponding numbered tasks, S1:1–3, S2:4–6, S3:7–9. Pedestrians (represented by 'X') will reach the red area by choosing to bypass two sets of obstacles (gray). The available paths in the scenario are numbered from 1 to 6. Black boxes on the left and right sides of the obstacle indicate signs of different sizes. For pedestrians within the yellow area, the local shortest path and global shortest path are named Route1 and Route2, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

area. In other words, pedestrians can stay straight, i.e., choose the same numbered route as in the previous step in Step2, or turn to another numbered route. By naming the areas for route choice and clearly defining the route options, we ensure a structured experimental setup that allows us to analyze participants' decision-making and wayfinding behavior accurately.

2.2. Experiment apparatus

In the development stage, we imported the 3D models created in Maya software (version 2021) software into Unity (version 2021.3.21f1c1) and implemented UI interface development and human–computer interaction functionalities using Visual Studio (version 2021). Regarding the hardware, the virtual reality platform was configured on a laptop (Dell Inspiron 16 Plus) with operation system: Windows 10, 64-bit, CPU: 12th Gen Intel(R) Core(TM) i7-12700H 2.30 GHz, RAM: 32G.

During the experimental stage, we set the screen resolution to 3072 × 1920 pixels and the screen refresh rate is 90 Hz. Through comparison with real-world observation results, this resolution ensures consistency with the field of view of pedestrians in reality. Previous research (Fu et al., 2021) has indicated that walking too slowly in a virtual environment can reduce engagement, while walking too quickly can lead to motion sickness symptoms. Likewise, considering the study setting is pedestrian wayfinding behavior under normal conditions and temporal factors, travel time and speed are not considered in this study. Therefore, during the experimental process, to balance efficiency and a good experience, we set the walking speed of the participants to 1.7 m/s, higher than the typical walking speed of pedestrians, which ranges from 1 m/s to 1.5 m/s. Based on the configuration above, this experiment can achieve greater flexibility and cost-effectiveness compared to immersive VR experiments.

2.3. Experiment task design

2.3.1. Three-dimensional wayfinding task

In the three-dimensional (3D) scenario, participants needed to complete a total of 9 tasks. In each task, participants took control of a simulated pedestrian positioned at an initial location within the starting area of the scenario. To introduce variability and generate different scenarios for participants to navigate, we manipulated the initial position of the pedestrian. The initial position of the pedestrian was randomized by selecting from 3 different horizontal positions, each with a lateral deviation of approximately 5 m. Additionally, we divided the entrance area into 3 vertical areas labeled as S1, S2, and S3 (Three square areas in different colors in Fig. 3). These areas were classified on the basis that pedestrians can access similar spatial information (2 alternative routes, obstacles of the same size et al.) and identical route conditions within them (pedestrians in S1 have their local shortest route as paths 1 or 2, and S2 corresponds to 3 or 4). Participants were required to complete 3 tasks within a randomly assigned location in each area (in total 3 x 3 tasks). This enables easy comparison of wayfinding results between areas and our validation results (see Appendix A) showed that this does not lead to significant differences in the results of local and global route choice.

During the 3D wayfinding tasks, participants navigated the virtual environment from a first-person perspective. We chose not to rely on specialized VR equipment for this study, opting for a more flexible and cost-effective approach. Due to the presence of numerous obstructing components in the 3D scenario, pedestrians had to navigate through the arranged facilities within the walkable area to reach their designated destination, which was controlled by mouse and keyboard. Throughout the experiment, we recorded the position of pedestrians within the scenario at one-second intervals, capturing detailed movement data.

2.3.2. Two-dimensional wayfinding task

To compare the impact of dimensional differences on pedestrian wayfinding behavior, participants were also required to complete the same wayfinding task in a two-dimensional (2D) perspective after finishing the task in the three-dimensional (3D) scenario. In order to facilitate this comparison, our platform provide both 3D and 2D views of the space. The position and orientation of the participant's pedestrian were displayed in real time on the 2D view, as depicted in Fig. 2. The process, requirements, and number of tasks in the 2D scenario wayfinding experiment were identical to those in the 3D experiment. Since we record the pedestrian's position information during the experiment, including the initial position, in the 3D experiment, the initial position of the same participant in each round of the 2D scenario was set to be the same as their position in the 3D scenario. This ensured consistency and allowed for a direct comparison of the participant's wayfinding behavior between the 3D and 2D perspectives.

2.4. Experiment procedure

The experiment procedure of the wayfinding experiment consists of 6 phases. A systematical presentation of the experiment procedure is shown in Fig. 4.

Phase 1 Participant training. Before the start of the experiment, participants were given instructions on how to manipulate the pedestrian using the keyboard controls and were informed of the specific objectives they needed to achieve within the virtual scenario. To be more specific, participants were instructed to imagine that they are undertaking a trip inside a transportation hub. To ensure that participants approach the experiments with equal familiarity and to eliminate any potential bias, they were not allowed to preview the experiments beforehand and participants have not traveled to the scenario in real life in the past. This approach guarantee that all participants are introduced to the scenario layout for the very first time during the official experiment session.

Phase 2 Position initialization. During the initialization phase, the character controlled by the participant was moved to a set initial position.

Phase 3 Task instruction. After the commencement of the task, the organizer conveyed instructions to the participants, acquainting them with the signage that indicates the destination to be reached. (such as B4-B5 small box in Fig. 3). And this principle guarantees that the destination was unique and unambiguous within the scenario.

Phase 4 Route choice. According to the instructions, participant manipulated the character to move. The coordinate data and visual images of the characters during the process were recorded.

Phase 5 Task completion. A task is considered complete when the specified destination is reached. The collection of behavioral data ceases, followed by a transition back to Phase 2.

Phase 6 Experiment termination. The experiment ended when participants completed the required number of task rounds (9

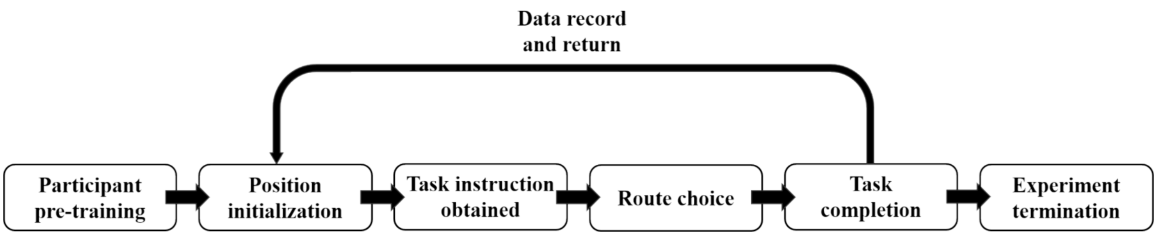

Fig. 4. Flowchart of Pedestrian wayfinding experiment.

rounds). Pedestrian trajectory and visual data recorded by the system is exported and further processed later.

2.5. Data collection

Using the VR platform, we conducted the pedestrian wayfinding experiment in 2023. We recruited 42 postgraduate students from Beijing Jiaotong University, aged between 21 and 28, with an average age of 23.27. The participants consisted of 20 males and 22 females. All participants have normal or corrected vision and were familiar with the operation process on the platform. They were recruited through social media and personal networks and compensated for their participation. Before beginning the experiment, participants were provided with information about the nature of the study and give their consent to participate by ticking a checkbox. It is important to note that we do not record any personal identifiers of the pedestrians during the experiment.

In our study, we collected behavioral data from participants during the experiment, specifically focusing on route choice data and visual field data in two dimensional types of scenarios. The route choice data includes information such as the coordinates of the pedestrians, the chosen route number, and the distance traveled. The visual field data consists of the images that participants see on the screen, which will be continuously recorded throughout the experiment.

3. Experimental data analysis and results

This section focuses on the analysis and results of pedestrian wayfinding experiments conducted under non-immersive conditions using desktop-based VR techniques. Both three-dimensional (3D) and two-dimensional (2D) virtual scenarios are utilized for data analysis and obtaining results. This study focuses on four factors that influence pedestrians, including the difference in length between global and local routes, lateral displacement of pedestrians relative to the destination, signage information, and the visual field information.

3.1. Route length difference

Previous studies have indicated a preference among pedestrians for shorter routes, as observed in field studies and virtual experiments (Liao et al., 2017). This study investigated the influence and differences of local and global route distances on pedestrian wayfinding behavior in large-scale transportation environments using both 3D and 2D virtual scenarios. To calculate the local distance, the research measured the Euclidean distance from the pedestrian's initial position to the midpoint of the path entrance in Area A. In VR environment, the computer-controlled pedestrians exhibited predominantly horizontal and vertical offsets. This allowed us to calculate the global distance by considering the Manhattan distance from the entrance to the endpoint position, in combination with the local distance. In 3D scenario, the local distance is determined by measuring the Euclidean distance between each participant's initial position in the scene and the midpoint of the six entrances. Recording ceased once the pedestrian entered the designated target area, and the global distance is calculated based on the recorded historical coordinates. The same distance calculation method is applied to 2D scenario.

Descriptive statistical results of selection ratio of different distance routes in different scenarios are shown in Fig. 5. The findings reveal that pedestrians, irrespective of the scenario dimension, demonstrated a strong preference for shorter routes, followed by the second and third shortest options. However, there are variations in the proportions of pedestrians selecting the local shortest and global

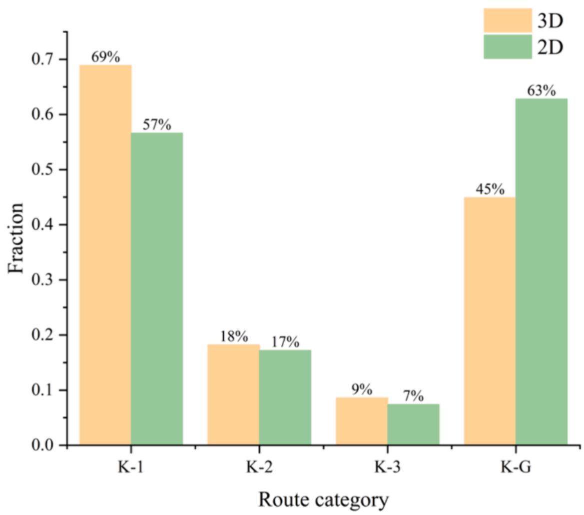

Fig. 5. The selection ratio of different distance routes in two dimensional types of scenarios. Where K-G represents the shortest path at the global scale, K-1 represents the shortest path at the local scale, K-2 represents the second-shortest route at the local scale, and so on.

shortest routes. In 3D scenario, a higher proportion of pedestrians (68.9 %) favored the local shortest route, while in 2D scenario, a higher proportion (62.8 %) opted for the global shortest route (refer to Fig. 5 for a bar chart depicting pedestrian route selection). These results suggest that the scenario dimension do influence pedestrian route choices. We believe that the primary reason for this result is the dimension of view and spatial knowledge, especially physical information such as local and global length of route. Therefore, pedestrians in 3D scenario primarily selecting the local shortest route, while those in 2D scenario demonstrated a higher inclination towards the global shortest route. Notably, there are no significant differences (χ^2 test, Sig. $= 0.239 > 0.05$) between the two scenarios in terms of the selection of the second shortest route based on local distance.

To further investigate pedestrian route selection behavior in different scenarios, the scene area is partitioned into 1 m x 1 m grids, and pedestrian position frequency distribution maps are created using recorded pedestrian coordinate data. Fig. 6 illustrates the frequencies at which pedestrians chose various routes within the scene. Considering the pedestrian choices in the three experimental groups (S1-S3) depicted in the first to third columns of Fig. 6 (S0 represents the overall statistics of the three sets of experiments S1-S3), it becomes evident that in 2D scenario, pedestrians predominantly favored the route with the shortest global distance, which

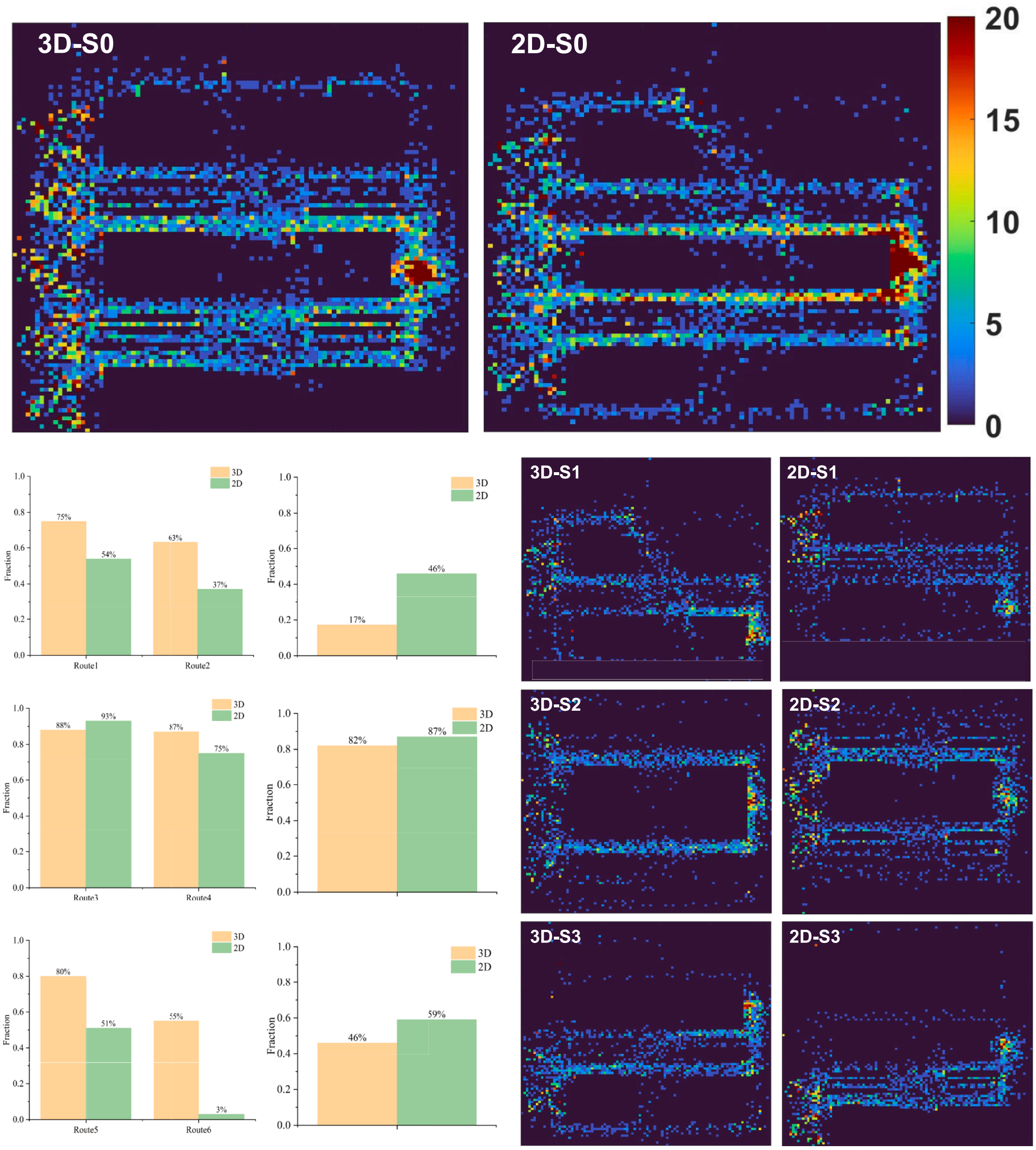

Fig. 6. Frequency distribution map of pedestrians' positions in S0-S3 in the VR scene. The field observation space is divided into a grid of 1 m × 1 m cells and the frequency of visits to each grid location is calculated. We also provide bar chart of the proportion of local and global shortest path pedestrian choices in S1-S3. The left bar shows the proportion of local shortest paths selected, and the right side shows the proportion of global shortest paths selected.

corresponds to route 3 and 4 located in the middle of the scene. On the other hand, pedestrians in 3D scenario exhibited a more balanced selection across different routes, without showing a distinct preference for the globally optimal route. Analyzing the statistical data, it can be inferred that in 3D scenario, pedestrians showed a higher frequency of choosing the local shortest distance route across all experimental groups compared to 2D scenario. This phenomenon is particularly pronounced in S1 and S3 groups, where pedestrians positioned on either side of the scenario displayed an increased frequency of selecting paths 1 and 6 in 3D scenario, as opposed to 2D scenario. Notably, paths 1 and 6 correspond to specific locally optimal routes for the given starting positions in the S1 and S3 experiments.

To investigate the influence of scenario dimension and starting position differences on pedestrian route preferences, the proportion distribution of pedestrians selecting the shortest paths is calculated based on the local and global distance differences. Fig. 5 shows that in 3D and 2D scenarios, the proportions of pedestrians choosing the shortest and second shortest paths are 87 % and 74 %, respectively. Therefore, the focus is placed on the distance differences between these two close paths, specifically the difference between the second shortest and shortest paths. The measured values of Δd and ΔD are plotted against the proportion of pedestrians choosing the routes in Area A under this distance difference.

Fig. 7 illustrates that as the local distance difference between paths increases, the proportion of pedestrians choosing the closer path gradually rises in both 3D and 2D scenarios. In terms of the global distance, pedestrians in both scenarios exhibited a decreasing trend in selecting the globally shortest path, with a more pronounced trend observed in 3D scenario. This decrease can be attributed to the lack of overlap between the local shortest and globally shortest route options in the majority of scenarios, further supporting the tendency of pedestrians to prioritize the local shortest distance in both 3D and 2D scenarios. In the 2D global scenario Fig. 7 (d), when the path difference is in the range of 10 m, the trend of the selection result for the global shortest route is not obvious, and the decreasing trend is gradually visible with the increase of the difference. This may be caused by the insensitivity of pedestrians to global

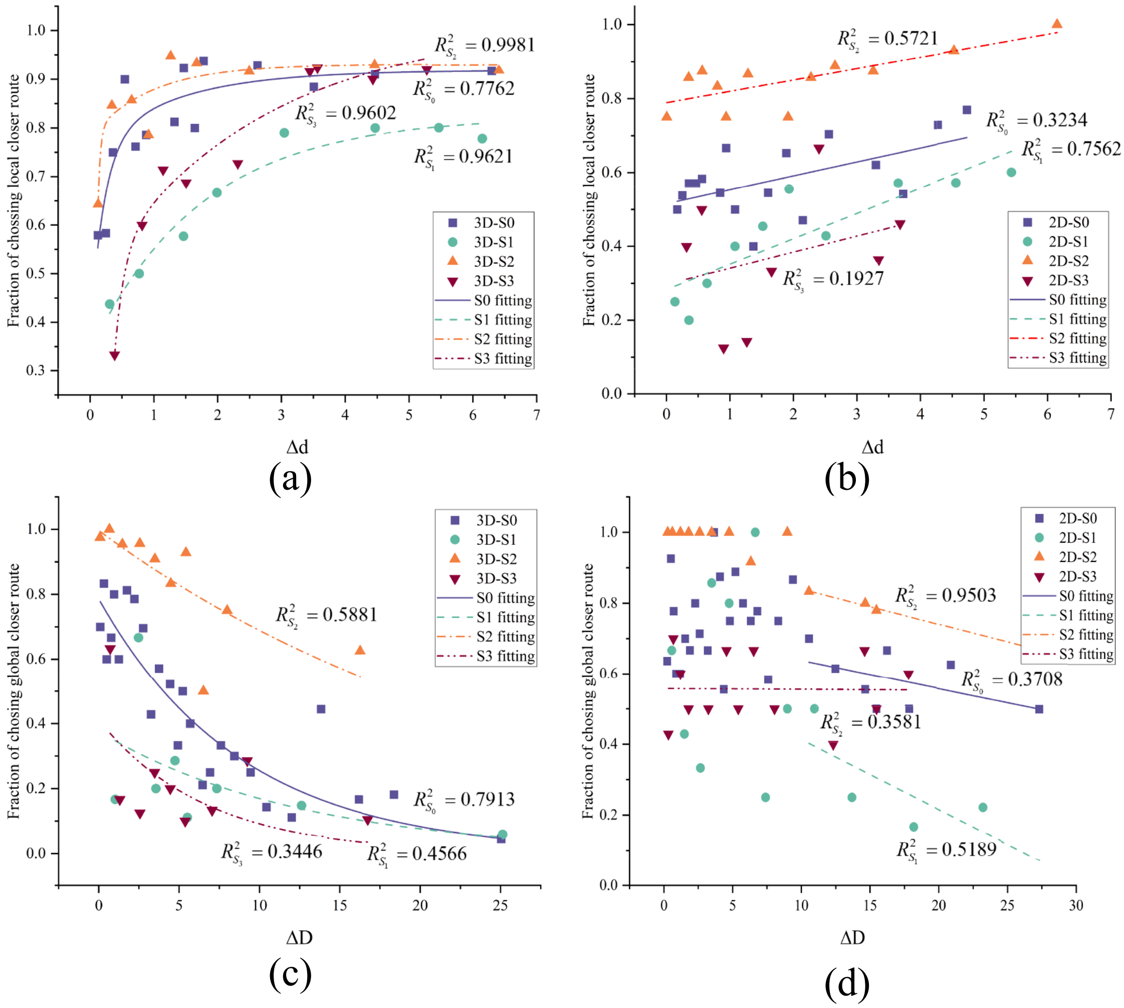

Fig. 7. Relation between difference in route local/global distance difference $\Delta d1\Delta D$ which are divided into bins of 0.5 m and 2.5 m respectively, and the fraction of pedestrians who choose the local/ global closer route in the virtual experiment. Different forms of scatter represent different experimental scenarios(S0-S3), where S0 denotes the overall statistics of the three sets of experiments (S1-S3).

length within a certain threshold (ΔD<10 m), and when the distance exceeds the threshold, the preference of pedestrians for global length gradually emerges.

Further analysis indicates that pedestrians in 3D scenario display nonlinear changes in the proportion distribution based on distance difference, while pedestrians in 2D scenario demonstrate an overall linear and consistent increase or decrease in the proportion of pedestrians choosing the shortest path as the distance difference increases. Our interpretation of this result is that pedestrians in the three-dimensional scenario are more sensitive to changes in spatial knowledge, This phenomenon is particularly significant for $\Delta d < 2$ and $\Delta D < 10$. Specifically, calculating the rate of change in the proportion of people choosing the shortest path as Δd and ΔD increase, the average rate of change in the 2D scene is only 14.8 % of that in the 3D scene. For the global scale, the 3D rate of change is 63.5 % of the rate of change in the 2D scenario. The route distance factor in the scene changes, and the fluctuation degree and proportion of pedestrian wayfinding behavior change in the three-dimensional scene are higher than those in the two-dimensional scene due to the same amount of change. Additionally, significant variations in wayfinding behavior are observed among different experimental groups (S1-S3) within the same scenario dimension.

To quantify and reflect these differences, a curve fitting method is employed on the scatter plot, and the fitting function is selected based on the highest R-square value. The general formulas and fitting results for the different scenario selections in this study are presented in Table 1 and Tables 2-5, respectively.

The fitting results indicate that when considering the behavioral differences among different experimental groups, the proportion of pedestrians choosing the shortest path (both local and global) in S2 remains significantly higher than in S1 and S3. This can be attributed to the fact that in S2, there is an overlap between the options of the local shortest and globally shortest path selections. However, the overall trend across all groups remains consistent. This suggests that changes in position do not lead to alterations in the principles of pedestrian route selection. A formal statistical evaluation of this effect is provided in Section 4.

3.2. Relative location difference

During the experiment, we find that in some cases, pedestrians choose routes in Area B that did not align with their paths in Area A (e.g., A1-B2). This observation is particularly noticeable in S1 and S3 experimental groups of 3D scenario, as depicted in Fig. 6. It is hypothesized that pedestrians, upon becoming aware of the specific location of their destination during the early or intermediate stages of wayfinding, exhibit a preference for paths with smaller deviations from the target area. The greater the initial deviation from the target, the stronger the inclination of pedestrians to converge towards the target area, leading to a deviation from the principle of selecting the shortest distance path. This phenomenon also accounts for the decrease in the proportion of pedestrians selecting the shortest path as the global distance increases, as discussed in Section 3.1.

In this study, the calculation of the deviation distance involved determining the difference between the vertical coordinates of pedestrians at the initial and target areas. The displacement of pedestrians relative to the previous time point is computed using the recorded historical coordinate data with a time granularity of 1 s, as shown in Fig. 8. Fig. 9 presents box plots illustrating the deviation distances in 2D and 3D scenarios. In 3D scenario, pedestrians displayed a more relatively balanced distribution of deviations (average 1.212, 1.337, 1.259; median 0.479, 0.443, 0.405) across the three transition areas. This can be attributed to the influence of physical conditions, such as field of view and observational habits, which introduce variations in pedestrians' spatial perception of object arrangements within the scene. 2D scenario provided all pedestrians with comprehensive global layout information, resulting in reduced differences in information among pedestrians and a more consistent behavior (average 1.402, 0.686, 1.634; median 0.422, 0.308, 0.512). As a result, differences in information among pedestrians contribute to variations in their wayfinding behavior, making pedestrian movement offsets statistically significant, especially in region G2 and G3 (G2: Wilcoxon signed-rank test, $Z = -5.768$, $P = 8.0219 \times 10^{-9} < 0.05$; G3: Wilcoxon signed-rank test, $Z = -6.248$, $P = 4.1512 \times 10^{-10} < 0.05$). However, in the pre-wayfinding G1 region, the difference in behavior due to dimensional changes is not significant (G1: Wilcoxon signed-rank test, $Z = -0.67$, $P = 0.946 > 0.05$).

Similar to the study in section 3.1, the relationship between the proportion of pedestrians choosing the shortest path and the consistency between the deviation distance and A-B path is examined. As depicted in Fig. 10, in 3D scenario, the proportion of pedestrians choosing the globally shortest route while maintaining consistency with A-B path gradually decreased (from 97 % to 28 %) as the deviation distance increased. But in 2D scenario, the impact is diminished (from 100 % to 77 %). A formal statistical evaluation of the influence of deviation distance can be found in Section 4.

3.3. Signage information

In large public spaces, the signage system plays a crucial role in conveying spatial information (Zhao et al., 2022). Signage systems

Table 1
The fitting function used in different scenarios and experimental scales, where y represents the proportion of pedestrians choosing the shortest length route, x is the distance difference and $A_1, A_2, A_3, t_1, t_2, t_3, a, b$ are parameters.

	3D	2D
Local	$y_1 = y_0 + A_1 e^{-x/t_1} + A_2 e^{-x/t_2} + A_3 e^{-x/t_3}$	$y_2 = a + bx$
Global	$y_3 = e^{a+bx}$	$y_4 = a + bx$

Table 2
The fitting parameter results of scatter data based on 3D local scale experiment.

	S0	S1	S2	S3
y_0	0.9182	0.8228	0.9182	1.0099
A_1	−0.2598	−0.1427	−0.3903	−2.6401
t_1	0.2091	1.7457	0.2091	0.1544
A_2	−0.1305	−0.1647	−0.0371	−0.1867
t_2	0.2091	1.7457	1.3194	2.5661
A_3	−0.1608	−0.1751	−0.1237	−0.3457
t_3	1.3194	1.7457	1.3194	2.5659
$R^2(y_1)$	0.7762	0.9621	0.9981	0.9602
Standard deviation	0.0775	0.0757	0.0784	0.0786

Table 3
The fitting parameter results of scatter data based on 2D local scale experiment.

	S0	S1	S2	S3
a	0.5158	0.2831	0.7892	0.2973
b	0.0376	0.0687	0.0307	0.0435
$R^2(y_2)$	0.3234	0.7562	0.5721	0.1927
Standard deviation	0.1129	0.1559	0.1141	0.1551

Table 4
The fitting parameter results of scatter data based on 3D local scale experiment.

	S0	S1	S2	S3
a	−0.2405	−0.9769	−0.0031	−0.8874
b	−0.1124	−0.0799	−0.0369	−0.1505
$R^2(y_3)$	0.7913	0.4566	0.5881	0.3446
Standard deviation	0.0824	0.0757	0.0515	0.1853

Table 5
The fitting parameter results of scatter data based on 2D global scale experiment.

	S0	S1	S2	S3
a	0.7172	0.6111	0.9397	0.5575
b	−0.0794	−0.0197	−0.0099	-2.0777×10^{-4}
$R^2(y_4)$	0.3708	0.5189	0.9503	0.3581
Standard deviation	0.0937	0.2309	0.0313	0.4435

provide spatial layout information, which helps reduce the complexity of the built environment and influences pedestrians' decision-making process in selecting routes, ultimately improving pedestrian flow capacity within the area. To examine the impact of information discrepancy resulting from signage and pedestrians' preferences for the information conveyed by different routes, participants in the experiment are instructed to choose routes and navigate to the destination based on the signage placed within the scene. To accurately assess whether pedestrians could perceive the wayfinding signage information in the research environment, the concept of Visual Cone of Availability (VCA) is employed (Xie et al., 2007). VCA of signage is simplified and defined as a circular area centered around the sign with a radius of R. Pedestrians are considered to receive the signage information if they are located within this circular area and the angle between their orientation and the line connecting them to the sign is less than 120° (Fisher et al., 1987). To determine the visible radius R of the signage in VR platform, participants are sequentially shown images of signs at distances of 50 m, 40 m, 30 m, and 20 m. The images are displayed on a full-screen (1920 mm × 1080 mm) and participants are asked to indicate whether they could perceive the sign information at each specific distance. The proportion results, presented in Fig. 11, revealed that at a distance of 20 m, 99 % of the participants could fully perceive the distant signage and obtain the information. However, beyond a distance of 30 m, less than half of the participants could see the sign clearly. In order to make this survey result more precise, we changed the interval to 5 m and found that the percentage of visualization remained high (more than 96 %) at a radius of 25 m. Based on these survey results, the visual radius for pedestrian vision is determined to be 25 m in this study.

The signage styles used in the study are illustrated in Fig. 12 and their distribution status in the experimental scenario has been demonstrated in Fig. 3. These signs consist of characters and numerical information that convey the locations and arrangement sequence of different buildings. Additionally, two different sizes of signs are employed. To aid pedestrians in distinguishing the signs and ensure a consistent scene layout, larger signs are positioned on the inner side of the scene, while smaller signs are placed on the outer side. During the experiment, each pedestrian is assigned a sign corresponding to their designated destination. They navigate to

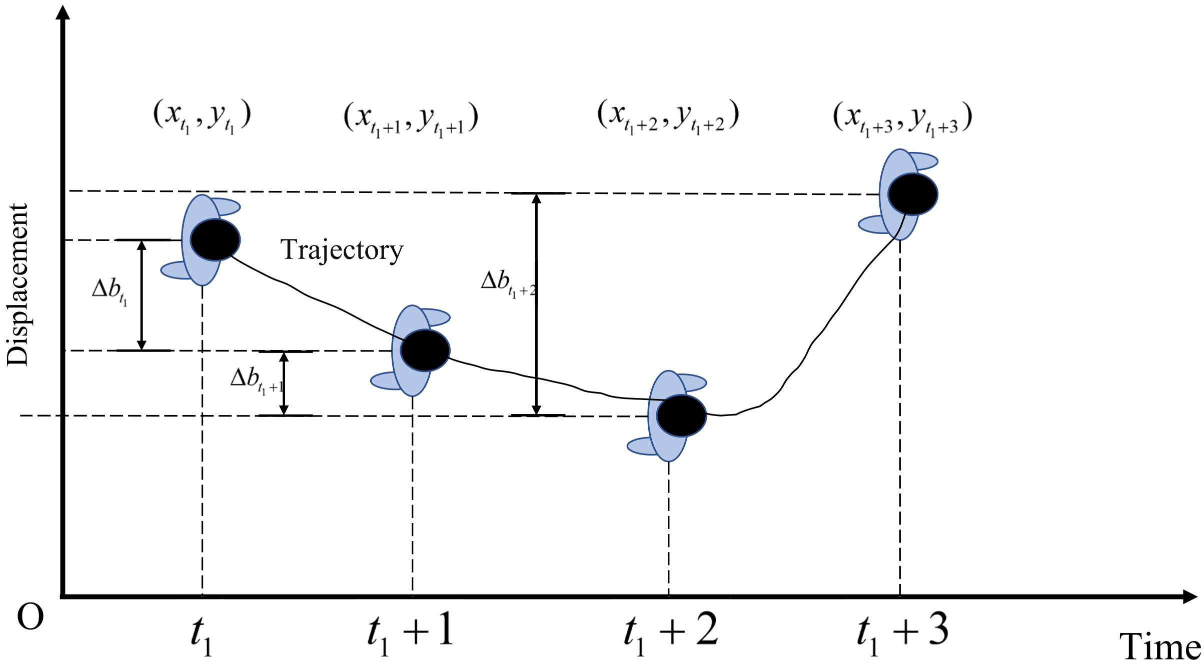

Fig. 8. Schematic diagram of real-time offset calculation method based on pedestrian coordinate, where $\Delta b_t = y_{t+1} - y_t$ represents the change of the pedestrian's position in the y-axis direction at time t. The orientation distribution of the 2D axes in the scene is shown in Fig. 3.

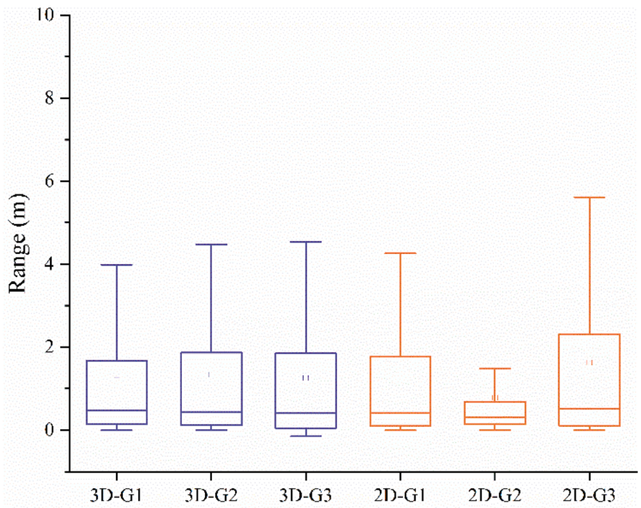

Fig. 9. Comparison of pedestrian offsets in areas with different dimensions, where G1 represents the initial region, G2 represents the transition region between regions A and B, and G3 represents the target region (see Fig. 4).

their destinations based on the signage information present within the scene. Throughout this process, the perceived features of the signs by pedestrians are recorded in a sequential order. In more detail, the order of change of the three features (number, character, size) of the signs along the route is recorded sequentially as the pedestrian walks from the starting point to the destination.

In the analysis of participants' wayfinding results, to quantify the amount of information obtained by pedestrians from different sign sequences, the information provided by the signs in the virtual environment is quantified using principles from information entropy (Shannon, 1948). Following these principles, the information content of the three types of signage information (i.e., numerical 1, character 2, size 3) in the experiment is calculated based on their probability distributions using Shannon entropy. The formula for calculating the information content is presented in Equation (1).

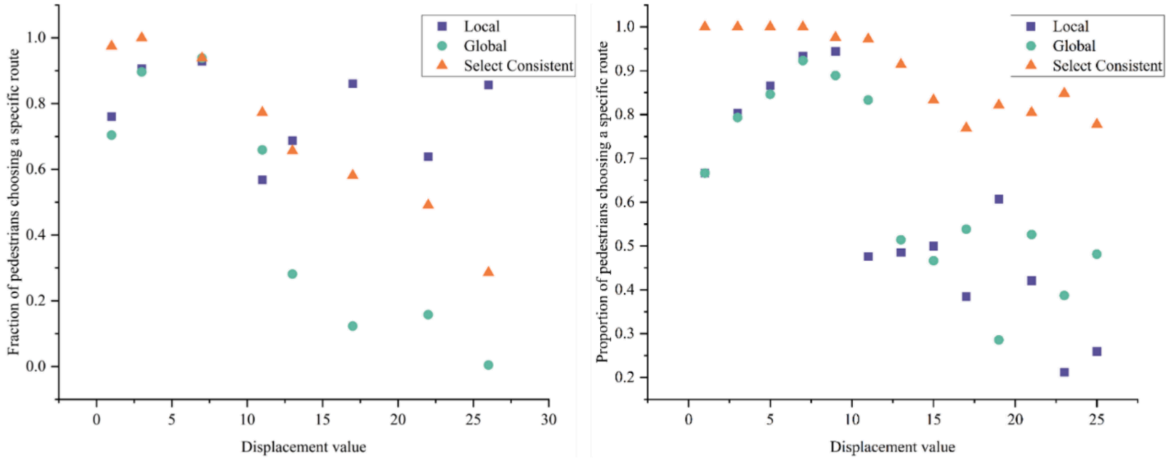

Fig. 10. Relation between offset distance and the fraction of pedestrians who choose the local/ global closer route in the virtual experiment.

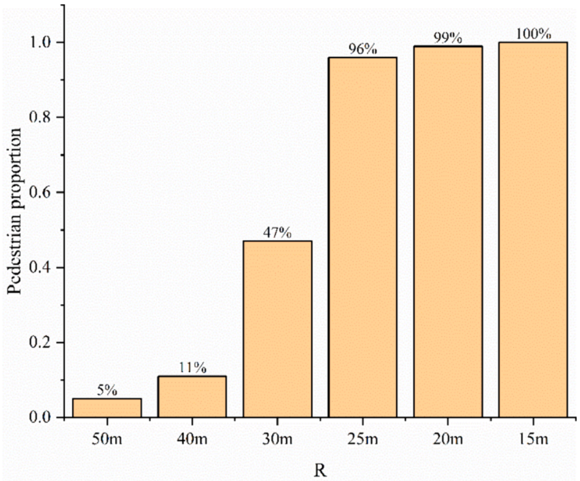

Fig. 11. Column chart of sign visibility survey for different pedestrian visual radius.

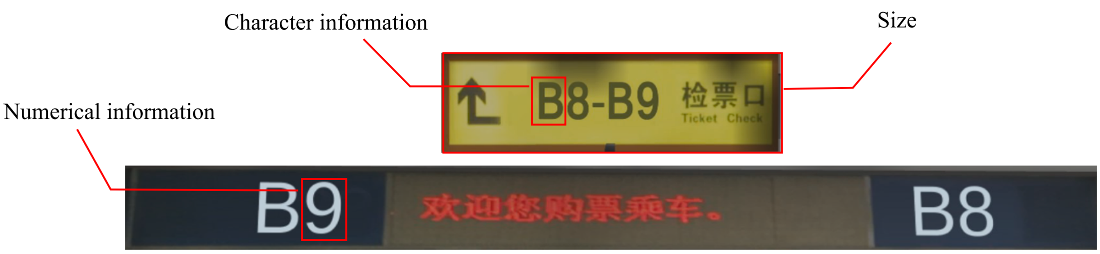

Fig. 12. Identifies information types in a virtual scenario.

$$H(X) = -\sum_{j=1} p(x_j)\log_2 p(x_j), j = 1, 2, 3 \tag{1}$$

where $p(xj)$ denotes the probability of the j^{th} type of signage information in the set X of pedestrian route choices, and $H(X)$ denotes the entropy of the probability distribution for a specific combination of signage types. The entropy measures the uncertainty or randomness in the distribution of signage information, with lower values indicating lower uncertainty. In this study, it is assumed that lower entropy corresponds to a combination of signage that helps pedestrians determine the specific location of their destination more easily. The information content of the signage in different experimental groups (S1-S3) within 2D and 3D VR scenarios is calculated. Fig. 13 illustrates that, especially in 3D scenario, size contributes the least to the overall information entropy, followed by number information. As the experiment progressed, the number and

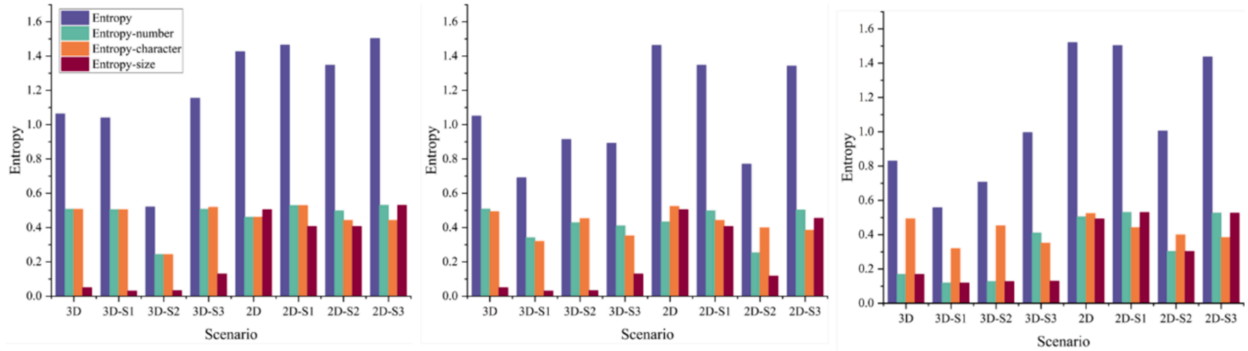

Fig. 13. Statistical graph of sign information entropy under different dimension scenarios and experimental settings.

character information entropy changed from being flat to maintaining higher values for the character single information type. This suggests that the size and number of the signs enable pedestrians to better locate their destination.

Comparing the different experimental groups, S2 exhibits lower overall information entropy compared to S1 and S3, indicating a smaller information discrepancy between S2 and the destination. Furthermore, the overall information entropy is higher in 2D scenario compared to 3D scenario, possibly indicating a lower demand for signage information in 2D scenario due to the availability of sufficient layout information in 2D plane. Further analysis of pedestrian signage preference reveals that in 3D scenario, 73.6%, 81.3%, and 64.2% of pedestrians choose the path with the lowest information entropy. In 2D scenario, although the proportions for each path are relatively balanced, the proportions for the path with the lowest information entropy reach 41.2%, 85.1%, and 41.8%. This suggests that pedestrians tend to make wayfinding decisions based on minimizing information entropy, aiming to reach their destination with the least information cost. However, the statistical results for two-dimensional scenario show the low dependency of pedestrian wayfinding process on signage, this may be due to the fact that 2D scenes have more global spatial knowledge. A formal statistical evaluation of the impact of signage will be discussed in Section 4. Also, the impact of signage information on pedestrians is diminishing as the experiment continue to advance.

3.4. Visual information

Pedestrian vision plays a vital role in understanding pedestrian wayfinding behavior, for it can provide a more realistic and accurate explanation of planning tendencies (Zhou et al., 2021). Hence, this study considers the visual information acquired by pedestrians in the virtual environment as a factor influencing their wayfinding behavior. Previous studies have indicated that during evacuation processes, pedestrians tend to prefer unobstructed routes (Guo et al., 2012). However, there is a lack of research on pedestrian wayfinding behavior under normal conditions. To address this, a significant number of opaque obstacles are strategically placed in VR environment to obstruct pedestrians' vision, including the location of the destination. In each experiment, participants are assigned different initial coordinates within the scene, resulting in variations in Feasible Visual Areas (FVA) available to them in the virtual scene. VR-based pedestrian experiments could help us record pedestrian vision from the screen (in this paper, the pedestrian

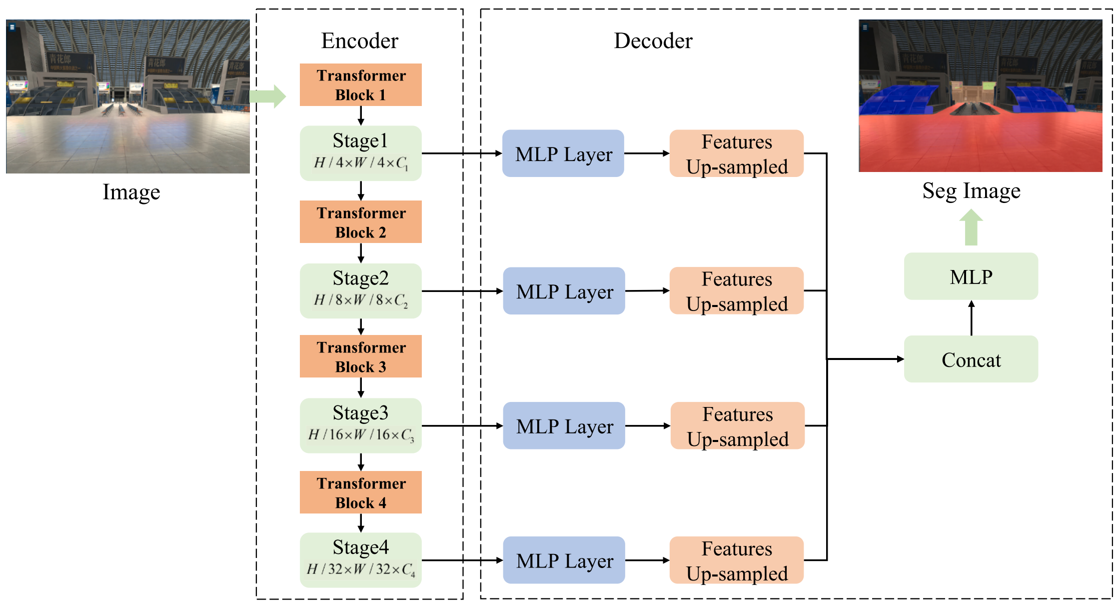

Fig. 14. A schematic diagram of semantic segmentation of pedestrian vision using the semantic segmentation framework based on SegFormer.

field of view is assumed to be the information about the scene presented by the screen to the participants, instead of the specific objects of interest to pedestrians captured by the eye-tracker), allowing for more accurate visual data acquisition compared to field experiments. To extract facility information in pedestrian vision, a semantic segmentation-based method is employed in this study. As the primary tool for understanding scenario visual (He et al., 2021; Wang et al., (2021b)), semantic segmentation is a widely-used method of dividing an input image into meaningful regions at the pixel level and assigning each region with a semantic label such as pedestrians, route and other objects. Our method involved calculating the proportions of various components (such as walkable areas, obstacles, destination signage, and overhead space along the path) within the vision, thereby quantifying pedestrian visual information. The objective is to investigate whether differences in the field of view, under normal 3D scenarios, influence pedestrian route selection.

For pedestrian m at the beginning of the n^{th} round of the experiment, the scene image $I_{m,n}$ presented within their field of view is analyzed. This study defined $Module_i$=(1,2,3,4,5) to represent the 5 object instances in pedestrian vision, including the shortest path, second shortest path, destination signage, obstacles, and overhead space on the walkable area. For each $Module_i$, $\theta_{Modulei}$ denoted the ratio of the visual area occupied by object i in the scene image $I_{m,n}$. The vector representation of $I_{m,n}$ and the quantification matrix for pedestrian visual effects are formulated as shown in Equations (2) and (3):

$$I = (\theta_{Module_1}, \theta_{Module_2}, \theta_{Module_3}, \theta_{Module_4}, \theta_{Module_5}) \tag{2}$$

$$M = \begin{pmatrix} I_{1,1} & \cdots & I_{1,n} \\ \vdots & \ddots & \vdots \\ I_{m,1} & \cdots & I_{m,n} \end{pmatrix} \tag{3}$$

To perform semantic segmentation, SegFormer framework, based on the Transformer architecture, is utilized in this study (Xie et al., 2021). SegFormer is selected for its simplicity, effectiveness, and robustness, which enable better detection of building edges within the field of view and reduce the occurrences of missed detections and false detections during the training process. Fig. 14 depicts the working principle of image semantic segmentation using the SegFormer framework. The field of view 200 images of pedestrians, captured during their walking process, are annotated, and six object categories are classified in each image. Each pixel is assigned a specific category label group during the training process, with the background being considered as the sixth category component. The experimental results demonstrated that utilizing the SegFormer framework for training achieved an average pixel accuracy of 92.55 %. The evaluation metrics for target detection accuracy are presented in Table 6, based on the obtained training results.

Fig. 15 presents the proportions of the five components (walkable areas, obstacles, destination signage, and overhead space on the walkable area) within the field of view for different 3D perspectives. Additionally, scatter graphs in Fig. 16 illustrate the distribution of the proportion difference Δp between the path and other components, along with the proportion of pedestrians selecting the path with the highest proportion. In 3D scenario, there appears to be a slight increase in the proportion of pedestrians selecting the path with a higher proportion as Δp increases. Moreover, an increase in the proportions of obstacles and overhead space on the walkable area positively influences the proportion of pedestrians selecting the path with the highest proportion. However, variations in the proportion of destination signage do not seem to substantially impact pedestrian path selection within the scene. Throughout the experiment, this study recorded the proportion of destination signage within the field of view and also noted the co-occurrence of the path and destination signage in pedestrian vision as a binary variable. Notably, among pedestrians who did not select the path with the highest proportion within their field of view, over 87.4 % of them made this choice because the destination signage is visible along their chosen route. This suggests that when pedestrians can see the destination signage in their visual field, it takes precedence in the path decision-making process over the proportion of the route within the visual field. In other words, when pedestrians lose sight of the destination and cannot determine its exact location, they prioritize maximizing the proportion of the path within their field of view during the decision-making process. Interestingly, the proportion of individuals in this group (i.e., those selecting the path with the highest proportion within the field of view when the destination is not visible) also exceeds 87 %. A formal statistical evaluation of this effect is provided in Section 4.

4. Pedestrian wayfinding model

In this section, the identified trends from the preliminary analysis are formally evaluated.

In the non-immersive VR simulation experiment, regardless of the scenario dimension (3D or 2D), the statistical results from Section 3.1 consistently reveal that participants, while controlling individual pedestrians, predominantly choose between two routes: the shortest path and the second shortest route. Consequently, to streamline the statistical analysis, the research narrowed the focus to

Table 6
Semantic segmentation performance measure index data.

Class	IoU	VOE	RVD	ASD	MSSD	Acc	Fscore	Precision	Recall	Dice
Object1	95.2	4.8	−1.0	2.41	1.92	96.15	97.54	98.97	96.15	97.54
Object2	95.13	4.87	−0.98	2.42	1.96	98.97	97.5	96.08	98.97	97.5
Object3	63.69	36.31	−9.72	4.87	14.21	71.58	77.82	85.25	71.58	77.82
Object4	87.89	12.11	−2.48	3.03	5.05	97.51	93.56	89.91	97.51	93.56
Object5	85.21	10.89	−2.59	2.74	4.78	91.34	93.21	88.53	95.68	94.2

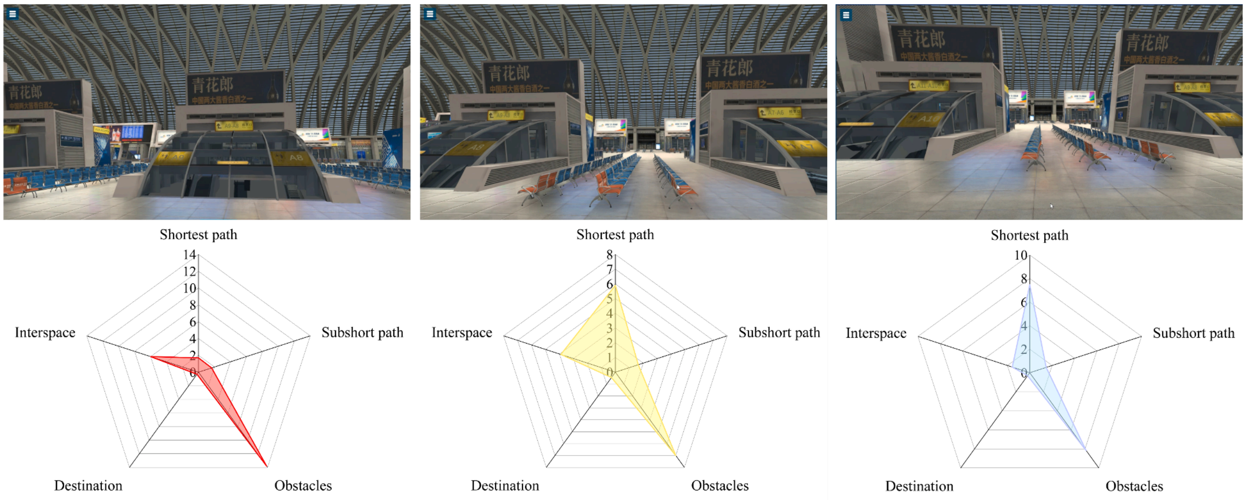

Fig. 15. Proportion radar map of five modules in pedestrian vision.

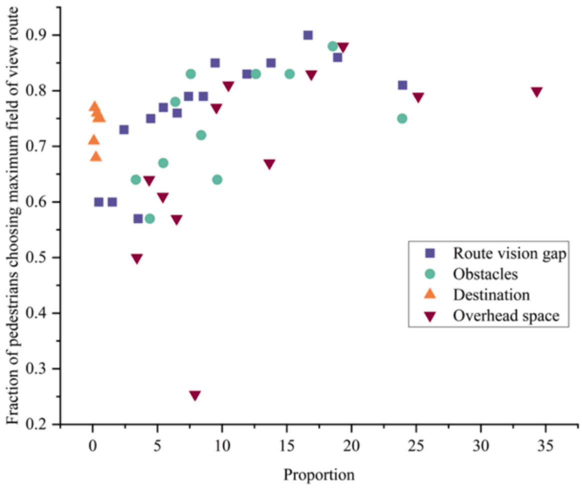

Fig. 16. Relation between module ratio and the fraction of pedestrians who choose the maximum field of view route in the virtual experiment. Route vision gap is the difference between the occupancy of the two routes in the vision.

binary choices, with 1 indicating the selection of the shortest path and 0 representing the selection of the second shortest path. Data related to behaviors involving the selection of other paths are excluded from the analysis.

To examine the impact of the factors discussed in previous sections on the binary outcome of whether pedestrians choose the shortest path, logistic regression is employed. This analysis is performed separately for different scenario dimensions, considering both

Table 7
Explain variable names and their definitions.

Parameter	Definition	Data type
d	The local distance difference of two routes	Real number
D	The global distance difference of two routes	Real number
bias	The lateral offset distance of the initial position and destination	Real number
information	Information entropy	Real number
p	Proportion difference	Real number between 0 and 1
appearance	The visibility of the destination in the path	Binary variables
pro_destination	The proportion of destination in vision	Real number between 0 and 1
pro_obstacles	The proportion of obstacles in vision	Real number between 0 and 1
pro_space	The proportion of space in vision	Real number between 0 and 1

the local shortest path and the global shortest path. Table 7 presents the names and types of all explanatory variables used in the analysis. The difference in distance between the two exits of routes in Area A, denoted as *d* and *D* for the local and global scales, respectively, is considered. Consistent with the recording method used in Sections 3.1, 3.2, and 3.3, this variable is always calculated as the subtraction of the shorter distance from the longer distance, ensuring a positive value. Additionally, the proportion difference of the measured path within the field of view is recorded and included in the analysis, along with distance deviation, information entropy of signage, visibility of the destination, and the proportion of other components within the field of view, serving as additional explanatory variables.

The assumption is that the data for the first and second individual choices are independent. To explore potential changes in participants' behavior over time, aside from the behavioral differences arising from dimensional variations, interactions between four primary explanatory variables (*d/D*, information, p, appearance) and categorical variables representing experimental scenario settings (S1, S2, S3) and scenario dimensions (3D, 2D) are considered. Each participant repeated experiments S1 to S3 three times under different initial conditions, resulting in 18 datasets per participant. Before formally starting the behavioral analysis, an analysis of the habituation effect on pedestrians as the experiment progressed is carried out (see Appendix B). Statistical analyses are conducted using SPSS 26 and Biogeme. Regression results (Table 8) on pedestrian wayfinding behavior found that dimensional changes had a significant effect on the generation of differences in wayfinding behavior, but changes in scenarios could still not be ignored. Moreover, the effect of visual information within 2D scenario is not significant, so the visual information (pro_destination, pro_obstacles, pro_space) is ignored in the modeling process of the 2D pedestrian wayfinding model. In the following sections, we will analyze the wayfinding models separately for two-dimensional and three-dimensional scenarios in sections 4.1. and 4.2., respectively. In section 4.3., we will compare the differences in wayfinding behavior resulting from dimensional variations.

4.1. Wayfinding model for 3D

Likelihood ratio tests (LR tests) are employed to assess the contribution of interaction terms to the statistical model. Separate tests are conducted for interactions between explanatory variables and the categorical variables (i.e., experimental settings and scenario dimensions) mentioned above. The results of 3D scenario revealed significant improvements in the statistical model for pedestrian choices of the local shortest path in 3D scenario when considering the interaction terms of the local path distance difference (LR test, $\chi^2 = 316$, $p = 4.1 \times 10^{-5}$), initial and final lateral deviation (LR test, $\chi^2 = 316$, $p = 4.9 \times 10^{-5}$), path information entropy (LR test, $\chi^2 = 316$, $p = 2.309 \times 10^{-64}$), and destination visibility (LR test, $\chi^2 = 128.153$, $p = 1.0391 \times 10^{-29}$). However, the interaction term of the proportion difference of the path within the field of view did not contribute to improvement (LR test, $\chi^2 = 210.172$, $p = 0.425$). The fitting results of the local path selection model in 3D scenario are summarized in Table 9.

The results indicate that the local path distance difference, lateral offset distance, information of signage, and visual field all influence individual pedestrians' route choices around obstacles. Among them, the differences in information content brought by signage type, distance, and the proportion of physical space within the field of view have a more pronounced influence (as indicated by the estimated parameters in Table 9). The negative parameter estimates for lateral deviation and information content suggest that increasing lateral offset distance from the initial point to the destination and an increase in information entropy resulting from the distribution of path signage lead to a decrease in pedestrians' inclination to choose the local shortest path. The interaction terms demonstrate that as the experimental settings progress, the effect size of distance difference increases in pedestrian wayfinding decisions. On the other hand, the interaction estimates for lateral deviation, signage information, and field of view are negative, suggesting that the effects of these factors on decision-making decrease as the number of pedestrian experiments increases. This result

Table 8
Calibration results of pedestrian wayfinding behavior model considering dimensionality and experimental scenario variations.

	Explanatory factor	Dimensional interaction		Scenario interaction	
		Parameter estimate	Sig.	Parameter estimate	Sig.
Local scale	d	0.358	2×10^{-6}	−0.001	0.979
	D	0.006	0.679	0.019	0.087
	bias	0.05	6×10^{-6}	−0.002	0.74
	information	−0.407	0.07	0.018	0.852
	p	0.047	0.036	−0.006	0.005
	appearance	0.344	0.074	−0.032	0.805
	pro_destination	2.235	8.8×10^{-5}	0.255	0.5
	pro_obstacles	0.06	3.58×10^{-4}	−0.004	0.727
	pro_space	0.046	4.41×10^{-4}	−0.003	0.742
Global scale	d	0.033	0.643	−0.014	0.755
	D	−0.141	7.2415×10^{-11}	0.026	0.035
	bias	−0.072	8.1403×10^{-9}	0.008	0.213
	information	−1.718	1.4389×10^{-13}	0.133	0.167
	p	−0.03	0.054	0.004	0.72
	appearance	−0.924	1×10^{-6}	0.125	0.323
	pro_destination	−2.554	4×10^{-6}	0.355	0.339
	pro_obstacles	−0.076	2×10^{-6}	0.005	0.606
	pro_space	−0.058	2×10^{-6}	0.004	0.611

Table 9
Statistical analysis of 3D local scale scenario route choice data, where d•Scenario, bias•Scenario, information•Scenario and appearance•Scenario are the interaction terms between experiment groups and factors.

Explanatory factor	Parameter estimate	t value	Sig.
Intercept	3.547	5.621	2×10^{-6}
d	0.303	3.456	0.001
bias	−0.034	−3.948	1.16×10^{-4}
information	−3.176	−5.929	2.2458×10^{-8}
p	0.008	0.211	0.832
appearance	−0.063	−2.755	0.006
pro_destination	0.686	0.887	0.376
pro_obstacles	8.857	1.721	0.086
pro_space	6.784	1.705	0.089
d•Scenario	0.265	3.938	1.12×10^{-4}
bias•Scenario	−0.042	−2.055	0.041
information•Scenario	−1.752	−2.076	0.039
appearance•Scenario	−0.172	−1.211	0.227

suggests that, under limited physical information and field of view conditions, the distance factor is the most influential information obtained by pedestrians within the scene, and its impact on decision-making is consistently reinforced in subsequent processes.

The statistical analysis of global pedestrian wayfinding behavior in 3D scenario followed the same approach. Likelihood ratio tests showed that neither deviation (LR test, $\chi^2 = 226.265$, $p = 0.445$), proportion difference of the path within the field of view (LR test, $\chi^2 = 210.172$, $p = 0.425$), nor their interaction terms with experimental settings improved the global path selection model. The results of the global path selection model in 3D scenario are summarized in Table 10. In contrast to the local-scale model, the influence of path distance difference on selection behavior is no longer significant in the global-scale model. Instead, factors related to the field of view, such as the proportion of obstacles within the field of view and path visibility, became more important. Moreover, the parameter estimates of the interaction terms indicated that the effect of global distance difference over time is no longer significant compared to the local distance difference. Although information still had a substantial impact on selection behavior at the global scale, its effect decreased as the experiment progressed. These findings suggest that pedestrians in a 3D perspective rely more on local information (such as local distance and early-stage signage information) due to obstacles and unfamiliarity with the scene. However, they exhibit less sensitivity to differences in physical information at the global scale. Additionally, the progression of the experiment led to a reduced demand for signage information.

4.2. Wayfinding model for 2D

Using the same analysis approach as in 3D scenario, there are no obstructing obstacles in 2D scenario that impede the field of view, pedestrians have a global view from top to bottom. Therefore, the impact of the field of view in 2D scenario is not included, and the elements related to the field of view are removed from the dataset. Only the relationship between spatial physical information (distance, deviation, signage) and path selection behavior is examined. Likelihood ratio tests indicated that the local-scale variables of path distance difference (LR test, $\chi^2 = 325$, $p = 0.443$) and lateral deviation (LR test, $\chi^2 = 325$, $p = 0.458$), as well as their interaction terms with experimental settings, did not improve the local path selection model in 2D scenario. Thus, only the information entropy of signage (LR test, $\chi^2 = 123.696$, $p = 5.7131 \times 10^{-23}$) and the interaction terms with experimental settings are retained in the regression analysis.

The results in Tables 11 and 12 indicate that in 2D scenario, the influence of distance difference and lateral deviation on pedestrian path selection is not significant. Pedestrian choices in 2D scenario can be described as path selection based on the principle of minimizing information entropy of signage. The estimates of the interaction terms suggest that as the experiment progresses, pedestrians' sensitivity to the demand for environmental information, such as signage, decreases. In contrast to the results in 3D scenario, the fitting results of the global and local models in 2D scenario show that the parameter estimates and intercepts of the various influencing factors are very similar.

4.3. Comparison of wayfinding models in different dimension

The scatter plot in Fig. 17 demonstrates the impact of incorporating both spatial knowledge and visual information as behavioral factors on pedestrian wayfinding. It reveals a substantial improvement in the predictive accuracy of the model. Notably, spatial knowledge exerts a more significant influence on behavior compared to visual information. When considering only the distance difference factor, the model's prediction accuracy remains generally below 71 %, with a particularly low accuracy of 56.6 % in 2D local scenario. However, by including signage and lateral deviation information, the prediction results are enhanced by approximately 20 %, except in 2D local scenario. The inclusion of visual information further improves prediction, highlighting the importance of considering all four types of information to gain a comprehensive understanding of pedestrian wayfinding behavior. This finding reaffirms the effectiveness of considering both visual and spatial information for understanding pedestrian route choice behavior. Moreover, the predictive performance is notably higher for 3D local and 2D global scenarios in comparison to the other two types, which can be interpreted as a result of maintaining consistency between the scenario dimension and the information dimension. A more detailed

Table 10
Statistical analysis of 3D global scale scenario route choice data.

Explanatory factor	Parameter estimate	t value	Sig.
Intercept	4.548	3.216	2.9586×10^{-7}
D	−0.136	−3.367	0.001
bias	−0.31	−3.965	9.1×10^{-5}
information	−6.661	−5.929	2.2458×10^{-8}
p	0.05	0.086	0.931
appearance	−2.294	−2.755	0.006
pro_destination	8.633	0.887	0.372
pro_obstacles	8.85	1.721	0.086
pro_space	6.876	1.705	0.089
D•Scenario	−0.002	−1.488	0.138
information•Scenario	−2.416	−2.076	0.039
appearance•Scenario	1.289	−1.211	0.227

Table 11
Statistical analysis of 2D local scale scenario route choice data.

Explanatory factor	Parameter estimate	t value	Sig.
Intercept	2.853	8.436	4.2556×10^{-12}
d	−0.093	−0.577	0.564
bias	−0.118	−7.254	3.6978×10^{-12}
information	−3.826	−9.624	1.9551×10^{-19}
information•Scenario	−0.67	−6.133	3.1573×10^{-9}

Table 12
Statistical analysis of 2D global scale scenario route choice data.

Explanatory factor	Parameter estimate	t value	Sig.
Intercept	2.933	6.241	0.087
D	−0.007	−0.606	0.545
bias	−0.111	−5.653	4.3207×10^{-8}
information	−3.6	−7.481	7.7313×10^{-13}
information•Scenario	−0.573	−3.924	1.28×10^{-4}

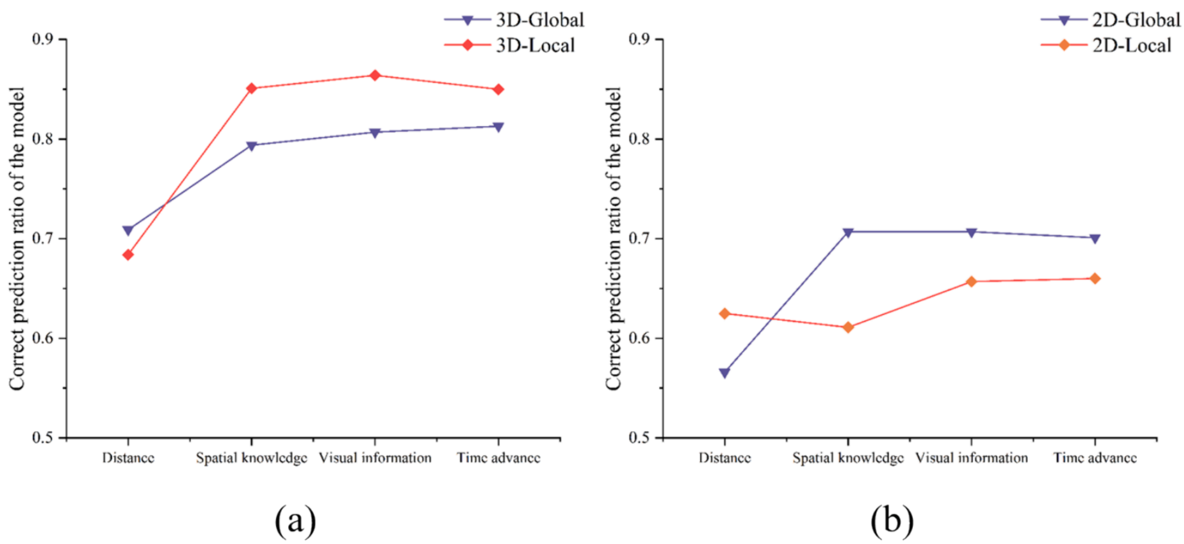

Fig. 17. The prediction results of route choice model considering different combinations of spatial knowledge and visual field information.

explanation is that in 3D scenarios, pedestrians are influenced by factors like occlusion and visual range. As a result, the environmental information acquired by pedestrians is limited, such as local distances and field of view information. Therefore, considering the predictive model based on the mentioned inputs yields better fitting and explanatory results in practical experiments compared to utilizing global information (global distances) or two-dimensional information (top view map). Similarly, the predictive performance of the two-dimensional model follows the same logic.

In order to compare the differences in pedestrian wayfinding behavior across different scenario dimensions and assess the varying effects of influencing factors, this study included the interaction terms of distance difference, lateral deviation, information entropy of signage, and scenario dimensions in the regression analysis. The results of the regression analysis are summarized in Tables 13 and 14. The estimated coefficients of the interaction terms indicate that, in comparison to 2D scenario, 3D scenario shows an increase in the effects of local path distance difference, lateral deviation, and information entropy of signage. However, the impact of global distance difference is lower in 3D scenario compared to 2D scenario. These findings suggest that as the scenario dimensions increase, pedestrians become more sensitive to local physical information and visual cues.Fig. 18.

5. Discussion

This research utilizes VR technology to construct virtual scenario that map realistic large public space and use them to study pedestrian wayfinding behavior. Two major contributions of this research are the consideration and quantification of the influence of spatial knowledge and visual information on pedestrian wayfinding and the comparison of pedestrian wayfinding differences in virtual scenes of different dimensions.

The first contribution of this study is to demonstrate that considering spatial knowledge and visual information is effective for understanding pedestrian wayfinding behavior. We found that over 68 % of the choices in the 3D scenario could be predicted by considering route distance, and the accuracy of the prediction results rose to 80 % when the two spatial knowledge factors of identification and location offset are added. This compares to 56.6 % and 70 % respectively in the 2D scenes. Considering the effect of visual information can further improve the model's prediction of path selection, especially for wayfinding behavior at local scales. Based on the prediction results of the model considering different combinations of factors, the following recommendations can be given for the selection of wayfinding experimental scenarios.

(1) We recommend that the experimental scenario dimension should be the 3D scenario, because the wayfinding model that considers factors in the 3D scene describes behavior better overall than the 2D scene, regardless of the combination of factors. As more factors are considered, the overall 3D prediction effect shows a tendency to be continuously optimized, and this optimization is significant.

(2) For the study of pedestrian behavior at the global scale, although the prediction effect in 2D scenes is slightly worse than that in 3D scenes, with the addition of factors such as signage and visual field information, the optimization trend is more obvious compared to 3D scenes. It is more beneficial to analyze and quantify the impact of changes in global-scale behavioral factors on route decision results.

(3) While for the study of pedestrian behavior at the local scale, we prefer to suggest the utilization of 3D scenarios. For it has a more sensitive trend and better predictive effect on the added spatial information factors.

For the second contribution of the study, the study validates and quantifies the difference in the effect of dimensionality on travel behavior by comparing pedestrian path choice behaviour in 3D and 2D scenarios. The results obtained from the experiments corroborate and expand upon existing findings (Borgers and Timmermans, 1986; Srinivasan et al., 2017) in terms of the choice of route distance scales. The parameter estimates for global and local distances also reflect a 'local selection tendency' in 3D and a 'global selection tendency' in 2D. This phenomenon can be explained by differences in the amount of spatial information available to pedestrians due to differences in dimensionality, resulting in different selection preferences. It is believed that the difference in the proportions will increase as the number of participants in the experiment increases. The results of the interaction term between the influencing factors and the scene dimension show that as the scene dimension increases, the influence of all factors, except for the global route distance, increases to varying degrees, especially the sign and route distance factors. The results of this study suggest that 3D scenarios are more suitable for experimental wayfinding models that take into account multiple factors. The loss of spatial information such as obstacle occlusion and first-person perspective in the 2D scenarios resulted in a greater entropy of the information available to the pedestrian in the scenes than in the 3D scenarios, i.e. the information to the destination is more readily available in the 2D scenarios, which also resulted in a less significant effect of many factors. Together, these contributions contribute to a better understanding of pedestrian wayfinding behavior in virtual scenarios and shed light on the impact of spatial knowledge, visual information, and dimensional differences in VR settings.

With the prevalence of smartphones, an increasing number of people choose navigation apps represented by Google Maps when traveling. They can choose to obtain the relative positions of themselves and their destinations in space through electronic maps in a

Table 13
Statistical analysis of local scale scenario route choice data.

Explanatory factor	Parameter estimate	t value	Sig.
Intercept	3.222	5.372	2.726×10^{-9}
d	0.347	3.456	0.001
bias	−0.034	−3.948	1.16×10^{-5}
information	−3.115	−5.929	2.2458×10^{-8}
d•Dimension	0.116	3.251	0.001
bias•Dimension	0.011	3.948	9.1×10^{-5}
information•Dimension	1.038	5.929	2.2458×10^{-8}

Table 14
Statistical analysis of global scale scenario route choice data.

Explanatory factor	Parameter estimate	t value	Sig.
Intercept	2.756	5.741	1.4617×10^{-7}
D	−0.123	−7.413	1.7577×10^{-12}
bias	−0.223	−14.318	3.9642×10^{-36}
information	0.938	5.785	2.1947×10^{-8}
D•Dimension	−0.041	−7.413	1.7577×10^{-12}
bias•Dimension	0.074	14.318	3.9642×10^{-36}
information•Dimension	0.313	5.785	2.1947×10^{-8}

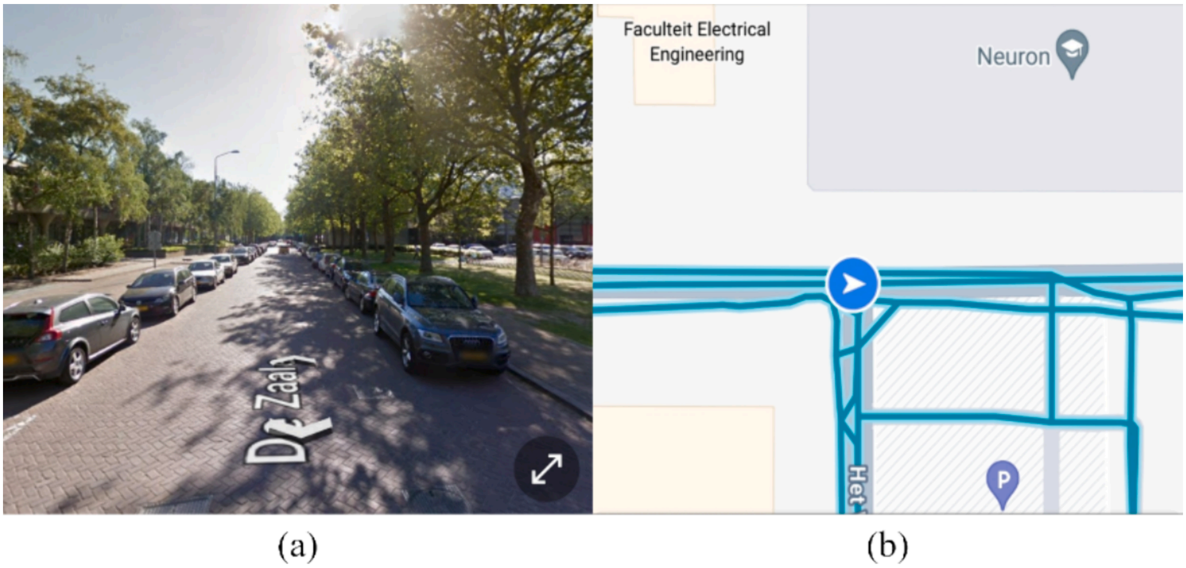

Fig. 18. 3D street view (a) and 2D electronic map (b) interface from Google Map APP.

two-dimensional view or street view in a three-dimensional view, and then actively select feasible walking routes and proceed. This phenomenon represents a change compared to the traditional pedestrian’s path selection pattern in three-dimensional space. This study reveals the mechanism of these selection differences, and the research results can provide a theoretical basis for optimizing both individual path recommendations at the micro level and crowd control in public spaces at the macro level. Specifically, as local shortest paths and global shortest paths often do not overlap, providing pedestrians using different navigation methods with paths featuring different distance characteristics under congested conditions can effectively reduce the traffic pressure on a single path and improve pedestrian travel efficiency. For developers of wearable augmented reality (AR) devices like Apple Vision Pro, understanding pedestrians’ preferences for different types of signage under different navigation format can help emphasize influential signage information in scenes selectively to users, such as emphasizing signage size and characters in three-dimensional maps. This can reduce information redundancy and improve user experience. For managers, providing different dimensional information to different groups entering a space at different locations and times can create information gaps for different groups, generating diverse walking schemes to avoid the crossing of pedestrian flows, thus effectively controlling the flow of people in the space and reducing congestion levels.

We hope that the results of this study will also provide effective recommendations for guiding the design of public spaces. The results of the parameter estimation of the interaction term between spatial knowledge and the experimental group settings show that the influence of physical attributes of paths such as distance and location offset on pedestrian wayfinding behavior is increasing as time progresses. In addition, as the previous study on location deviation found a tendency for pedestrians to prioritize lateral displacement, especially where the starting point is far from the destination. We believe that the design of large public spaces, represented by transport hubs, should set the lateral paths connecting entrances and exits wider than those perpendicular to them, in order to improve the accessibility of the space.

6. Conclusions

In this study, we employed non-immersive VR experiments to investigate pedestrian wayfinding behavior in large public spaces. Using a VR experiment platform, we conducted experiments that focused on the impact of route distance, deviation, signage information, and visual field on pedestrian wayfinding behavior. To enhance the predictive power of wayfinding models, we utilized mathematical statistics analysis and deep learning tehniques. We employed information entropy theory and Segformer, which is a deep learning-based semantic segmentation model, to quantify the identification information and visual field information obtained during the pedestrian wayfinding process. Additionally, we examined and quantified the effects of scenario scale and dimension on pedestrian behavior, analyzing the differences that arise in these aspects. By combining these approaches, we aimed to optimize the prediction effectiveness of wayfinding models and gain insights into the influence of various factors on pedestrian wayfinding behavior in virtual environments.

To further refine the pedestrian wayfinding experiment, there are several areas that require attention. Firstly, the selection of participants should be expanded to include individuals of different age groups. This will help ensure a more diverse sample and improve the generalizability of the experimental results. In the future, regarding the influence of pedestrian visual information on wayfinding, we find that it is necessary to further explore the influence of different objects in the visual field on wayfinding behavior with the help of eye-tracking instruments, focusing on the visual attention objects of pedestrians in the process of movement rather than the distribution of global objects in the field of view in order to achieve the purpose of the improvement of the current experimental instruments. While some objects may be present within the field of view, without eye-tracking data, it cannot be confirmed whether the pedestrian's gaze remains focused on them during the wayfinding process. Therefore, incorporating such factors into the analysis may introduce potential interference. Secondly, it is important to enhance the functionality of the VR platform. This can be achieved by incorporating additional elements into the scenario, such as computer-controlled pedestrians or other participants controlling pedestrians. By introducing these components, the impact of factors like route congestion and social relationships, such as group dynamics, can be studied more comprehensively. This will provide a deeper understanding of the various factors that influence pedestrian wayfinding behavior in virtual environments. Furthermore, ongoing efforts should be made to expand the capabilities of the experimental platform. This may involve incorporating advanced features like realistic crowd simulations, interactive signage systems, or dynamic environmental changes. These enhancements will enable a more realistic and immersive experimental setting, further improving the effectiveness and validity of the results. By addressing these areas of improvement, future research can refine the pedestrian wayfinding experiment, allowing for a more comprehensive exploration of the factors influencing pedestrian behavior in virtual spaces.

CRediT authorship contribution statement

Zhicheng Dai: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Dewei Li:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Yan Feng:** Writing – review & editing, Investigation. **Yuming Yang:** Data curation. **Long Sun:** Data curation.

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.

Data availability

Data will be made available on request.

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Appendix A. . Validation of the effect of differences in initial pedestrian positions and area lengths on route choice consistency

Table A.1 shows the significance test for difference in route choice results between equal length division of area and unequal division (same as experimental scenario in Fig. 4). The test results show that the different divisions do not produce two significantly different (variance significance > 0.05, Sig. > 0.05) pedestrian route choice outcomes both in 3D and 2D scenario.

Table A.1.

Significance test for differences in pedestrian wayfinding behavior results obtained from different area division (ES: equidistant division, S: division used in this study) approaches.

	Local scale selection		Global scale selection	
	variance significance	Sig.	variance significance	Sig.

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		Local scale selection		Global scale selection	
		variance significance	Sig.	variance significance	Sig.
3D	S1-ES1	0.596	0.789	0.065	0.127
	S2-ES2	0.148	0.474	0.235	0.556
	S3-ES3	0.908	0.954	0.114	0.212
2D	S1-ES1	0.146	0.299	0.696	0.271
	S2-ES2	0.056	0.347	0.303	0.609
	S3-ES3	0.492	0.733	0.626	0.779

Since in this study, the initial pedestrian position is randomly generated in the region, conducting a correlation test between the initial pedestrian position and the path selection results to exclude its effect on the consistency of route choice is necessary. Table A.2 shows that The initial positions of randomly distributed pedestrians in the region show a low correlation with the final wayfinding results. Thus it is reasonable to be confident that the setup of our experiment does not significantly affect the consistency of behavioral choices.

Table A.2.

Correlation analysis between pedestrian position and route choice behavior.

		Local scale selection		Global scale selection	
		Correlation	Sig.	Correlation	Sig.
3D	S1	−0.174	0.114	−0.156	0.1
	S2	−0.129	0.115	−0.105	0.112
	S3	−0.119	0.148	−0.186	0.142
2D	S1	−0.071	0.5	−0.145	0.165
	S2	−0.149	0.061	−0.047	0.561
	S3	−0.132	0.192	−0.201	0.054

Appendix B. . An analysis of learning effect on the outcome of pedestrian wayfinding behavior

Table B.1- B.3 presents the results of the significance analysis on the influence of learning effects from the experimental on the pedestrian route choice outcomes. The results of significance analysis below local and global scale selection denote the significance of the effect of the independent variables on the choice of local and global shortest paths, respectively. The results show that both physical knowledge and visual information, except for signage information, show low significance on route choice. It is therefore reasonably certain that learning influence about the scenarios will not have a large impact on the results of the later experiments. The analysis for labeling information is also consistent with the findings of dependency reduction in 3.3.

Table B.1.

Analysis of the influence of habituation effects on the significance of pedestrian path selection results in 3D scenarios.

Explanatory factor	Local scale selection		Global scale selection	
	χ^2	Sig.	χ^2	Sig.
d•round	313.577	0.48	313.988	0.474
D•round	316	0.474	316	0.474
bias•round	316	0.474	316	0.474
information•round	122.029	5.4343×10^{-7}	227.268	8.221×10^{-23}
p•round	301.464	0.546	307.954	0.442
appearance•round	35.056	0.006	84.455	6.1383×10^{-11}
pro_destination•round	185.102	0.268	207.741	0.041
pro_obstacles•round	303.079	0.407	307.283	0.343
pro_space•round	305.501	0.385	307.283	0.358

Table B.2.

Analysis of the influence of habituation effects on the significance of pedestrian path selection results in 2D scenarios.

Explanatory factor	Local scale selection		Global scale selection	
	χ^2	Sig.	χ^2	Sig.
d•round	325	0.474	325	0.474
D•round	325	0.474	325	0.474

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Explanatory factor	Local scale selection		Global scale selection	
	χ^2	Sig.	χ^2	Sig.
bias•round	325	0.474	325	0.474
information•round	184.983	1.8842×10^{-13}	172.625	1.0674×10^{-11}
p•round	320.929	0.428	314.302	0.532
appearance•round	156.303	0.144	117.386	0.279
pro_destination•round	202.794	0.393	199.48	0.457
pro_obstacles•round	320.929	0.475	320.721	0.478
pro_space•round	320.929	0.475	320.721	0.478

Table B.3 Analysis of the influence of habituation effects on the significance of pedestrian path selection results in full experimental process.

Explanatory factor	Local scale selection		Global scale selection	
	χ^2	Sig.	χ^2	Sig.
d•round	636.678	0.496	638.983	0.47
D•round	641	0.481	641	0.481
bias•round	641	0.481	641	0.481
information•round	312.666	4.4338×10^{-17}	406.793	2.8791×10^{-30}
p•round	620.83	0.506	630.915	0.393
appearance•round	273.071	0.113	141.577	0.059
pro_destination•round	385.427	0.244	394.147	0.158
pro_obstacles•round	622.991	0.436	626.208	0.401
pro_space•round	627.313	0.4	624.191	0.434

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