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Review visual attention and spatial memory in building inspection: Toward a cognition-driven information system

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ABSTRACT

With the increasing complexity of modern buildings, it is becoming more challenging for the professionals in the Architecture, Engineering, and Construction (AEC) industry to effectively digest complex engineering and design information and develop an accurate spatial memory that is critical to their daily tasks. As emerging visualization technologies, such as Virtual Reality, are considered as a promising solution, there is a pressing need to understand the mechanism by which different information visualization methods affect AEC task performance. Cognition literature has discovered a strong relationship between attention and memory development, but little has been done to understand how the visual attention patterns during the design documents review affect the effectiveness of spatial memory in AEC tasks. To fill the knowledge gap, this paper presents a human-subject experiment (n = 63) to test how spatial knowledge is acquired in a building inspection task and how the different visual attention patterns affect the development of spatial memory. Participants were asked to review the design information of a real building on campus. To trigger different attention patterns, they were randomly assigned to one of the three groups based on the forms of information given in the review session, including 2D, 3D, and VR groups. After a brief review session, participants were asked to go to the real building to identify discrepancies (based on memory) that were intentionally inserted by the authors. The inspection performance was used to evaluate the spatial memory development. The results indicate that in general there is a positive relationship between test subjects' visual attention (fixation time) and spatial memory, but the increasing rate varies across the three groups, suggesting that visual context plays a critical role in the development efficiency of spatial memory. The findings also indicate that the visual attention – spatial memory relationship may be mediated by the use of different spatial knowledge acquisition strategies. This study is expected to contribute to the construction information technology literature by setting the cornerstone of a cognition-driven information system that tailors into the spatial cognitive process of AEC professionals.

1. Introduction

Attributed to the advances in architectural and engineering technologies, modern buildings are becoming increasingly complex [1], featuring a large number of available shapes, dimensions, spatial positions of internal building components and complex topology relationships of rooms [2], posing significant challenges to the design, construction and maintenance of modern buildings. While the new design features and building technologies have greatly improved our indoor living experience, it is becoming more difficult for the AEC industry professionals to effectively digest increasingly complex engineering and design information in important tasks such as building inspection [3–5]. One of the challenges caused by the increasing complexity of information in typical AEC tasks relates to the effective development of spatial memory, i.e., the memory of storing and manipulating visuospatial information such as locations, orientations, and frames of reference in the space [6]. Spatial memory plays a critical role in many space-related judgement and decision-making tasks related to buildings [7,8]. For instance, building inspectors rely on spatial memory to establish the base for comparing the differences between the as-built systems and the original designs [9]. In emergency situations, responders need to build an accurate spatial memory of the unfamiliar

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space in a short period of time for the indoor navigation [10]. Given the increasing spatial complexity of modern projects, and the emerging (while underexplored) methods of displaying relevant information (e.g., virtual reality for design communications), it is critical to understand the development, retention and retrieval mechanism of spatial memory for AEC tasks.

So far, the cognitive science literature has discovered a strong relationship between attention and memory development in general [11–13]. Nonetheless, little has been done to understand how visual attention (when reviewing engineering and design information) affects the spatial memory development in the AEC tasks. Even if we can find a positive visual attention-spatial memory relationship, as suggested by the cognitive science literature, a further investigation is still needed to explain why this relationship exists, i.e., the mechanism in which visual attention improves spatial memory development for AEC tasks. Understanding the general visual attention-spatial memory relationship, as well as the underlying mechanism behind it will greatly help the industry develop intelligent information systems that enhance spatial memory development, and eventually, the performance of critical AEC tasks.

Based on a comprehensive review of the cognitive science literature, we propose to investigate spatial knowledge acquisition strategies as a potential explanation for the positive visual attention-spatial memory relationship. *Spatial knowledge acquisition* represents specific methods a person relies on to build the spatial memory [14–16]. When a person presents in a completely new environment, she/he tends to rely on landmarks (e.g., a special plant or certain significant signages) at beginning to navigate (landmark knowledge acquisition). As the exposure time increases, many people will attempt to memorize the relative sequences of these landmarks (route knowledge), and ultimately, will try to develop a cognitive map to abstractly model the layout of the environment in mind (survey knowledge). This sequential and hierarchical process of spatial knowledge acquisition may present different strategies that are critical to the effective development spatial memory in AEC tasks.

To cumulate evidence about the visual attention-spatial memory relationship, and the role of spatial knowledge acquisition strategies in this process, this paper reports the findings of a building inspection experiment. Participants (n = 63) were required to review design information for a short period of time, and then finish a set of building inspection tasks. In order to trigger different visual attention patterns and spatial knowledge acquisition strategies [17], three information formats (2D, 3D, and VR) were used in the review. A novel eye-tracking system was developed to collect gaze movement data across different groups. The remainder of this paper will introduce the background, the experiment, and the findings.

2. Literature review

2.1. Engineering and design information in AEC projects

Amid the fast development of visualization technologies, different information display methods are introduced in the daily tasks in the AEC industry, such as 3D representations (e.g., laser scanning point cloud and BIM), and Virtual Reality and Augmented Reality (VR/AR) technologies [18–21]. The impact of these visualization methods on human spatial cognition is still not fully understood, and as a result, literature tends to present conflicting findings. Some researchers found that the emerging visualization technologies improve performance of typical AEC tasks [22–24], possibly due to the additional information captured by the semantically-rich presentations. Dünser, Steinbügl, Kaufmann and Glück [25] conducted a large-scale study (215 students) to investigate the potentials of VR/AR methods for improving human spatial ability. In addition to confirming the positive impacts of VR/AR methods on spatial ability improvement, they found that the added visual display features such as stereoscopic and head-tracked views could significantly improve test subjects' ability to identify gaps among different visual geometries [26,27]. Other studies found that VR can improve the sequential memory for arranging 3D objects in a complex spatial layout [28], or enhance memory about spatially distributed information [29], suggesting that VR helps the memory development in spatial ability-based tasks. In the AEC literature, Sweany, Goodrum and Miller [22] investigated how the format of engineering deliverables affects craftworkers' performance. They compared the impacts of 2D plans, 3D CAD models, and 3D mockup models on the performance of a pipefitting task, and found that the 3D groups outperformed the 2D group in both task accuracy and efficiency. They found that this conclusion was still valid after controlling the factor of individual differences in spatial cognitive ability. Verghote, Al-Haddad, Goodrum and Van Emelen [30] also examined the impacts of 2D drawings and 3D models on indoor wayfinding performance. They found that 3D models seemed to benefit the test subjects' wayfinding performance the most in comparison with the traditional 2D drawings.

In contrast, evidence also indicates that 3D or VR representations are not better than the traditional 2D drawings in certain situations, possibly due to the added cognitive burden for processing additional information such as textures, colors, orientations [31–33]. For instance, Bliss, Tidwell and Guest [34] compared the benefits of using 2D blueprints and VR models in an indoor navigation task. Although in general subjects trained with VR models and 2D blueprints outperformed those without training, there was no significant difference between the VR and blueprint groups in the both navigation speed and accuracy. Dadi, Goodrum, Taylor and Carswell [23] examined how 2D and 3D engineering information affect cognitive load. The result did not find any significant difference among the three information formats (2D drawings, 3D CAD models, and 3D mockup models) in both task performance and mental workloads. As an effort to resolve the disagreement, this study aims to investigate the cognitive process affected by the use of different information visualization methods. The most relevant process that will be investigated is the *spatial knowledge acquisition*.

2.2. Spatial knowledge acquisition and built environments

Acquiring spatial knowledge from the surrounding environment is a critical process of creating spatial memory [14]. The spatial knowledge can be hierarchically categorized into three main stages, which are landmark knowledge, route knowledge, and survey knowledge [17]. The landmarks are defined as the unique and distinctive objects at fixed locations in the environment [14]. Landmark knowledge is the knowledge of identifying and memorizing landmarks based on their shapes, sizes, colors, and contextual information in the environment [35]. With that said, the landmark knowledge is the fundamental process for forming spatial knowledge [17]. People can incidentally recognize the landmarks and unconsciously build their landmark knowledge through the navigation in the environment [15]. The process of acquiring landmark knowledge usually does not need much mental efforts. Siegel and White [17] found that even very young children were able to identify landmarks.

Route knowledge is a more advanced strategy for spatial knowledge acquisition. Route knowledge is encoded as the knowledge of memorizing the sequences of landmarks or locations from one location to the other location [17]. People can gain route knowledge either from a map or from a navigation experience [36]. The process of developing route knowledge requires a higher mental effort, and thus practices are helpful for the acquisition of route knowledge by navigating in the environment [37].

Lastly, survey knowledge is the process to mentally abstract the configurational information as a map-like representation of the environment [14]. It is the last and the most mentally demanding spatial knowledge acquisition method. People can gain survey knowledge either from a map study or from real-world exposure to the environment [35]. van Asselen, Fritschy and Postma [15] found that route knowledge and survey knowledge coexisted in the process of spatial memory development. They further found that the spatial information representation methods of the environment could significantly affect the process of spatial knowledge acquisition. Subjects who learnt from the map outperformed others in developing the survey knowledge. On the other hand, subjects who learnt by navigating in the environment performed better than others in developing the route knowledge [15,36]. Cognitive science literature has found the relationship between spatial knowledge acquisition strategies and spatial memory development effectiveness in navigation tasks [30,33,38–42], but little has been done to inform a conclusion in AEC applications. Most AEC literature focuses on the application of environmental cues, such as landmarks for spatial ability-based tasks (e.g., indoor navigation in large-scale buildings) [43,44], but a deeper understanding of the spatial knowledge acquisition and its impacts on spatial memory is not yet available. This study will set the foundation of the investigation into the cognitive basis of the visual attention – spatial knowledge acquisition – spatial memory process.

3. Research methodology

As illustrated in Fig. 1, a building inspection experiment (n = 63) was conducted to investigate the correlation between visual attention and spatial memory, as well as the role of spatial knowledge acquisition strategies in this process.

In the experiment, each participant was given five minutes to review and memorize the design of an unfamiliar building, and then go to the real building to identify discrepancies between the design and the real observations within 15 min. Without losing the generality, 28 discrepancies were designed in this experiment including architectural discrepancies (e.g., missing windows and doors), structural discrepancies (e.g., changing locations of columns), and mechanical discrepancies (e.g., missing air vents). Both quantities and locations of the selected building components were intentionally changed in the models (2D, 3D, and VR). To trigger the use of different spatial knowledge acquisition strategies, participants were asked to review the design in one of the three ways: (1) a 2D drawing, (2) an interactive 3D model, and (3) an immersive VR environment. Eye tracking was deployed to measure participants' gaze positions as an indicator of their visual attention patterns. For the 2D and 3D groups, the Tobii eye tracker 4C mounted to the monitor was used. For the VR group, participants' gaze movement data was recorded by an eye tracker embedded in the VR Head Mounted Display (HMD).

Three indicators were selected to capture participants' visual attention and spatial memory in the review and inspection task, including review fixation time, effective attention ratio, and building inspection score (BIS). To calculate effective attention ratio and review fixation time, the 28 discrepancies were used as the areas of interests (AOIs) that directly related to the building landmarks. Review fixation time is defined as the aggregated duration (in seconds) that subjects spent on each AOI. This indicator represents participants' attention relevant to the buildup of the spatial memory about the building. Effective attention ratio is defined as the percentage of participants paying attention on the AOIs versus the total review time (max. 5 min). BIS is calculated as the correct discrepancy identifications minus wrong discrepancy identifications in the inspection session. In other words, there is a

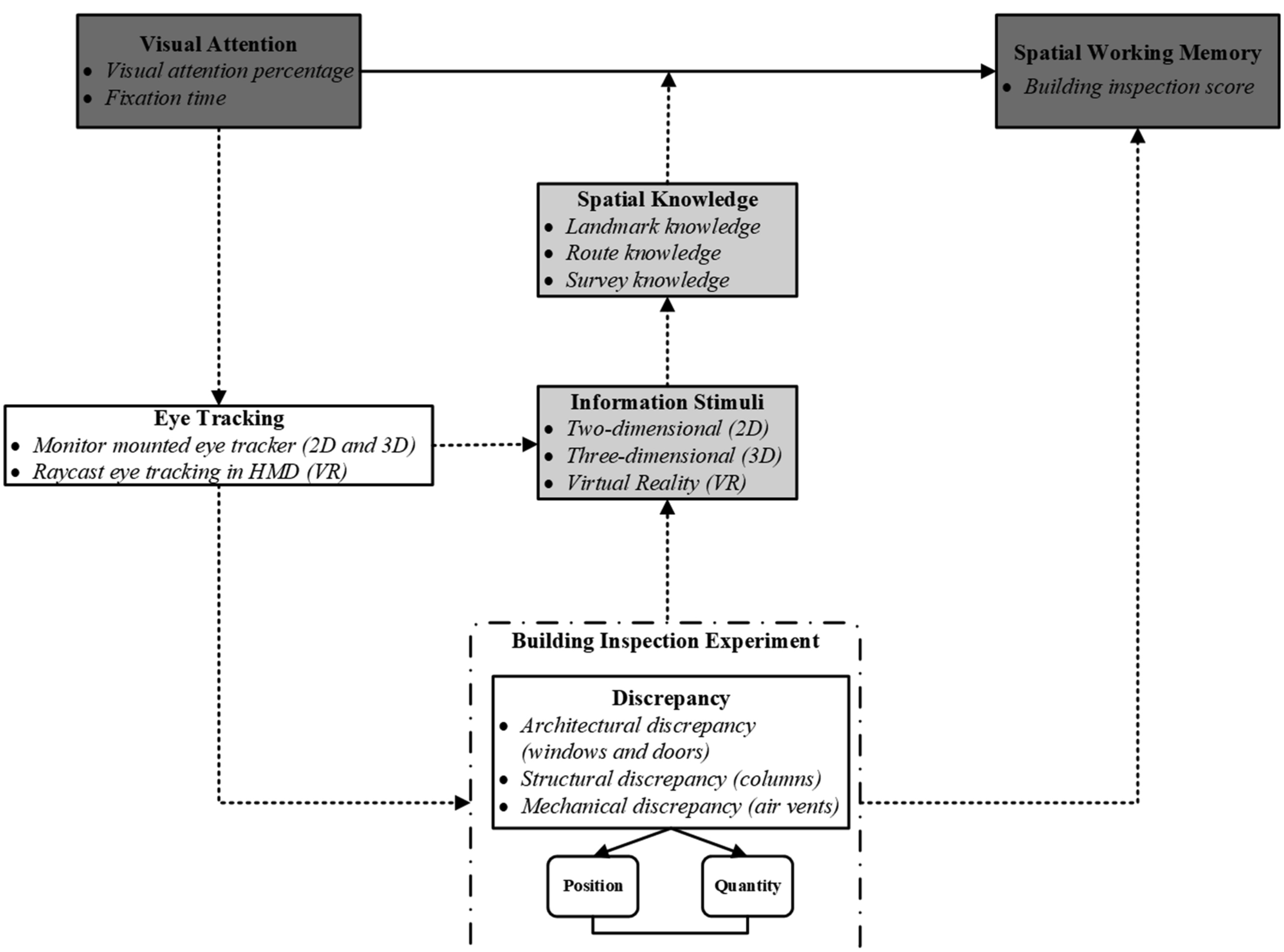

Fig. 1. Research Framework.

Table 1
The list of performance indicators in the experiment.

Indicator	Unit	Equation
Review fixation time	Second (s)	$T = \sum_{i=1}^{n} t_i$ *t_i is the fixation time of one area of interest (AOI) for each gaze visit. n is the number of gaze visit of one AOI. T is the aggregated fixation time of one AOI*
Effective attention ratio	Percentage (%)	$P = \sum_{j=1}^{k} T_j / T_{total}$ *T_j is the aggregated fixation time of one AOI. k is the number of AOI. T_{total} is the total review time. P is the visual attention percentage*
Building inspection score (BIS)	N/A	BIS = correct identifications-wrong identifications

penalty for any wrong identification to prevent participants from randomly guessing the discrepancies in the inspection session. BIS was used as a direct indicator of participants' spatial memory. Table 1 lists indicators in the experiment.

4. Experiment design

4.1. Eye tracking for visual attention assessment

We used eye tracking as the main instrument to collect participants' visual attention data across the three groups. Literature has shown the effectiveness of using eye tracking to investigate human perception and cognitive processes [45,46]. We developed and implemented a novel interactive eye-tracking system that works with all 2D, 3D and VR environments. For the eye tracking in 2D and 3D group, the Tobii eye tracker 4C mounted to the monitor [47,48] was used. The accuracy of the Tobii eye tracker 4C is within a radius of 0.5 in. from the gaze positions recorded on the monitor [49] and the operating distance is 20 to 37 in. from the monitor [50]. A building layout drawing was shown on the screen for the 2D group. Similarly, an interactive 3D model was shown on the screen for the 3D group. For the 3D group, the participants used the WASD keys on the keyboard to control the navigation including moving forward, moving backward, and moving left and right in the 3D model. Participants also utilized the mouse to change the field of view and rotate the 3D model. In the training session, the participants in the 3D group were asked to practice the use of this navigation method. As for the interaction in the VR model, the participants used an Xbox joystick to control their navigation and used their physical body rotation to control their movement directions. The interactive 3D model was designed to provide a third-person navigation experience for the participants, while, the VR environment was designed to provide an immersive walking experience. Gaze position and camera position data was recorded by the system at a frequency of 90 Hz. At the end of each experiment trial, the system automatically generated a CSV file with all raw data. For eye tracking in 3D and VR groups, we developed an innovative system using the Raycast function of Unity game engine. Raycast technique [51] was utilized to record the three-axis gaze position data and camera position data at the frequency of 90 Hz. An invisible ray shoots from the center of the participants' camera or gaze focus point on the screen, and returns a three-axis vector value when it collides with any virtual object in the 3D model [52]. Similar techniques were successfully implemented in the computer graphics literature to render camera directions or paths. We also developed a visualization function to playback the gaze movements based on the CSV files. To achieve all these functions, the Tobii software developer's kit (SDK) and the application programming interface (API) provided by Unity were used with C# programming [53]. The VR headset we used in the study was Oculus Rift Consumer Version 1 (CV1) [54]. The eye tracking system used in the experiment was developed with the Unity 3D-5.6.3f1 version. The models were developed based on Francis Hall at Texas A&M University. Fig. 2 shows the review sessions and eye tracking function of the three groups.

4.2. Virtual models as the testbed

Francis Hall at Texas A&M University was selected as the testbed for the building inspection experiment. Only the first floor was used in the experiment to control the difficulty level of the task for a better feasibility of the experiment. Fig. 3 (a) illustrates the 2D floor plan used to build the VR model. The VR model includes architectural, structural, and MEP system. A BIM-based multi-user VR platform [55,56] was used as the study instrument for this experiment.

We intentionally designed 28 discrepancies for the inspection that spread evenly in the model. In order to cover different types of discrepancies, they included three categories: architectural discrepancies, structural discrepancies, and MEP discrepancies. The architectural discrepancies included those related to windows and doors (e.g., the number of the windows/doors or the position of them). The structural discrepancies were associated with columns and beams (e.g., the number of the columns/beams or the position of them). The MEP discrepancies related to supply diffusers. Table 2 lists the details of the 28 discrepancies. In brief, there were 13 architectural discrepancies (five window discrepancies and eight door discrepancies), six structural discrepancies, and nine MEP discrepancies. Fig. 3(b) illustrates all discrepancies on the 2D drawing. The blue circles represent the architectural discrepancies, the red circles represent structural discrepancies, and the green circles represent MEP discrepancies. Meanwhile, in order to control the amount of information given to the participants, the building components on the ceiling and furniture were not modified. Fig. 4 show some examples of architectural and structural discrepancies between the models and the real building.

4.3. Experiment procedure

The inclusion criteria of the experiment recruitment was that participants had never been to Francis Hall before the experiment and they had basic knowledge about building designs. The task required participants to find as many discrepancies as possible. The experiment consisted of six sessions: (1) pre-questionnaire, (2) cube test (spatial cognition ability test), (3) training session (to familiarize with the eye tracking systems), (4) review session, (5) building inspection session, and (6) post-questionnaire and interview session. The pre-questionnaire session (5 to 10 min) was designed to collect participants' basic demographical information such as age, gender, major, degree level, and previous game and VR experiences. The cube test session (5–10 min) was designed to evaluate participants' spatial cognition abilities as the baseline for their task performance. The cube comparison test developed by the Educational Testing Service (ETS) was used for assessing participants' spatial cognition abilities. It is widely used for evaluating participants' spatial cognition in previous AEC literature [22,30]. The training session (5–10 min) was designed for participants to familiarize with the eye tracking devices, navigation functions, and the virtual environment. Participants were asked to calibrate their eye movement with the eye tracking system, where the investigator ensured participants' eye movements to be accurately captured by the eye tracker after the calibration trails. The participants were also given instructions about the navigation functions. For the 3D group, participants were

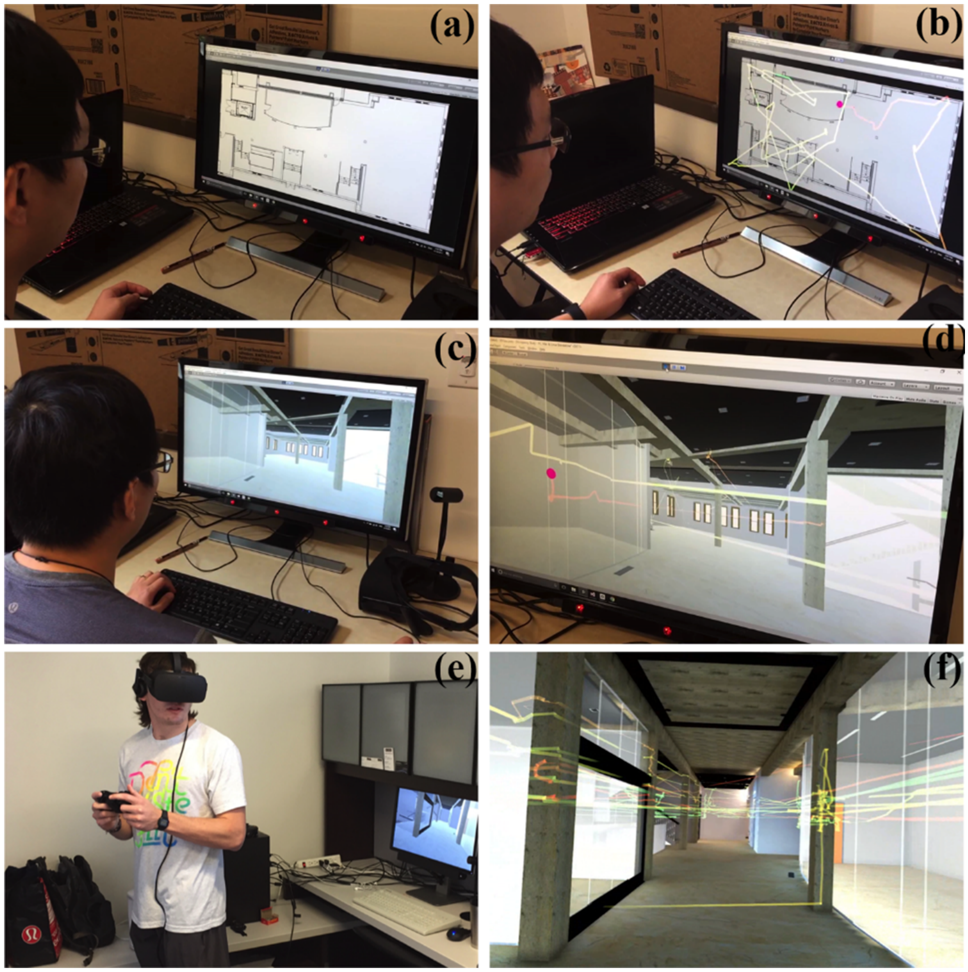

Fig. 2. The eye tracking in different groups. (a) recording gaze focus when reviewing a 2Ddrawing; (b) the playback of gaze movement on the same drawing; (c) recording gaze focus when reviewing an interactive 3D model group; (d) the playback of gaze movement in the same 3D model; (e) recording gaze focus in VR; (f) the playback of gaze movement in VR.

instructed to use a keyboard and mouse to navigate and change their field of view (FOV) to interact with the 3D model. For the VR group, participants were taught to utilize an Xbox joystick to control their navigation and use their physical body rotation to control their movement directions in the virtual environment. The review session (5 min) was used for participants to review and memorize the layout and details of the building. Participants were randomly assigned to one of the three groups depending on what information they were given (2D, 3D, and VR). Five minutes was limited for the review session as some participants may feel sickness (nausea, headache, dizziness, and lightheaded) for 10 min or more in the VR environment based on our previous studies. The participants were also informed that there would be 20 to 30 discrepancies in the building. They were required to find as many discrepancies as they could, and their performance would be compared with the other groups. The purpose of providing such information was that we wanted to motivate the participants in the inspection task. After the review session, participants were immediately asked to go to the real building site to identify discrepancies that were different from what they reviewed (15 min). The starting point of the inspection was the entrance of building to be consistent with the setups in the 3D and VR review sessions. The investigator of this experiment accompanied the participants to help participants record the time points when they found each of the discrepancies. The participants were also asked to briefly describe the discovered discrepancies with a data collection sheet. To reduce random guessing during the inspection, participants were told that there was a point penalty if they identified a wrong discrepancy. At the end of the experiment, participants were asked to fill out a post-questionnaire and provide comments and feedback for the experiment, including ease of control, presence, sickness, and attention (subjective evaluations). The entire experiment procedure took approximately 60–90 min for each participant. Fig. 5 shows different groups of participants utilizing the system to review the building.

5. Results and data analysis

5.1. Participants

A total of 63 participants (35 males, 28 females) participated in the experiment, including 10 undergraduate students and 53 graduate students. All participants were recruited via university email lists. They were from a variety of disciplines, with most of them being civil engineering, construction management, and architecture students. Participants' ages ranged from 19 to 39, and the median age was 26. Their previous video gaming and VR experience was also collected as it could affect their VR task performance [57]. The participants reported their previous video gaming and VR experiences as 11-point Likert scale (0- no experience, 10-a lot of experience). The average gaming experience was 4.68/10 and the average gaming time per week was 2.33 h. The average VR experience was 2.79/10. The results indicated that most participants had few VR experience. All participants claimed that they had never been to the building before the experiment. According to the cube test score for each participant, an ANOVA test

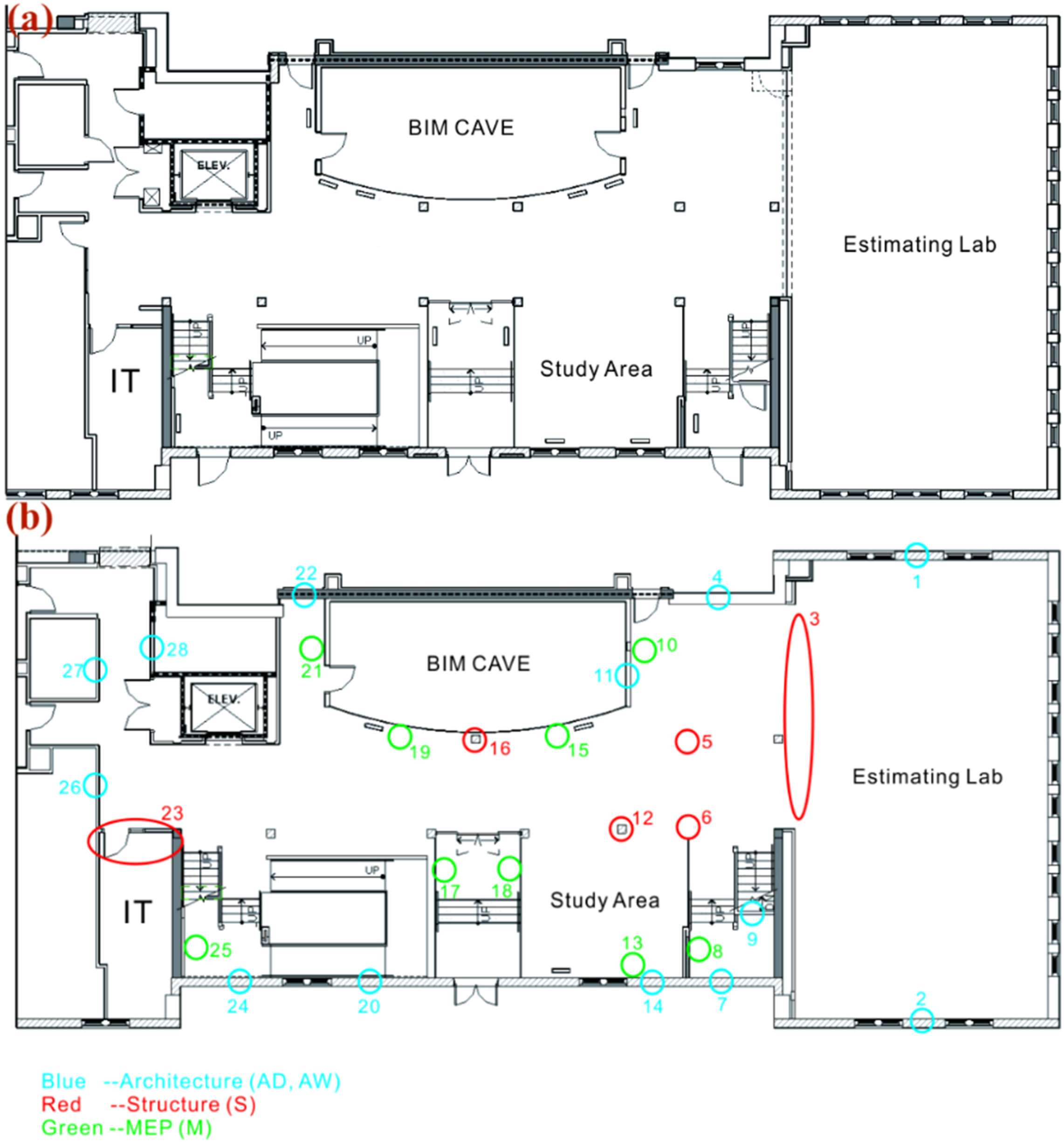

Fig. 3. The 2D floorplan of the building. (a) The original floorplan. (b) The modified floorplan.

(normality assumption was supported by the Shapiro-Wilk test) found that there was no significant difference ($p = 0.63$) in the cube test score across the three groups, which indicated that participants had a similar spatial ability level across the three groups. At the same time, in order to rule out individual differences, we randomly assigned 30 participants in each group. According to the Hogg and Tanis' Probability and Statistical Inference [58], the choice of $n = 30$ is a rule of thumb for a switching from a small sample size to a big sample size, supporting the statistical findings. Table 3 summarizes the demographic information of the participants.

5.2. Results of building inspection (BIS)

We first examined if the three groups performed differently in the inspection task. BIS was used as the performance indicator of this experiment. BIS is calculated as the correct discrepancy identifications minus wrong discrepancy identifications in the inspection session. The purpose of designing penalty is to reduce participants' random guessing during the inspection. We found that the design of the penalty helped reduce the random identifications during the building inspection experiment. We also found that wrong identifications could affect the analysis in a negative way more seriously than the missed detections, as participants tended to randomly report detections when a penalty did not exist in our pilot study. Random reports may increase “accuracy” because of simply more chances to guess. Therefore, we introduced the penalty to prevent random guesses. The average numbers of wrong identifications in 2D, 3D and VR groups were 2, 1.95, and 2.29 respectively. After removing three outliers according the Mahalanobis analysis, 20 participants in each of the three groups were used for the analysis (60 total). The 2D group had $M = 10.5$ with $SD = 4.03$, the 3D group had $M = 16.1$ with $SD = 3.28$, and the VR group had $M = 15.3$ with $SD = 4.11$. According to the Shapiro-Wilk tests of normality, BIS' of the three groups were normally distributed. The data met the requirements one-way ANOVA. We found a significant difference ($p < 0.0001$) in participants' BIS' across the three groups. A pairwise comparisons test for all pairs-Tukey-Kramer HSD test found differences between 2D group and 3D group ($p < 0.0001$), between 2D group and VR group ($p < 0.001$); but did not find a significant difference

Table 2
List of discrepancies.

Discrepancy ID	Discrepancy Description
1	Missing window on the north side of estimating lab
2	Missing window on the south side of estimating lab
3	Curtain wall missing in estimating lab
4	Window missing near estimating lab
5	Column missing between estimating lab and BIM Cave
6	Column missing on the left side of the right stairwell
7	Right exit door missing
8	Air vent missing near the right exit door
9	The door of crawl space missing
10	Air vent missing on the right side of BIM Cave
11	Dooring missing on the right side of BIM Cave
12	Column wrong position in the study area
13	Air vent missing in the study area
14	Window missing in the study area
15	Air vent missing on the right front side of BIM Cave
16	Column missing in front of BIM Cave
17	Air vent missing on the left side of the front entrance door
18	Air vent missing on the right side of the front entrance door
19	Air vent missing on the left front side of BIM Cave
20	Window missing near the ramp area
21	Air vent missing on the left side of BIM Cave
22	The door of Roger entrance missing
23	The layout of the IT helpdesk is wrong
24	Left exit door missing
25	Air vent missing near the left exit door
26	The door of bid room missing
27	The door of the storage room missing
28	The door of the electrical room missing

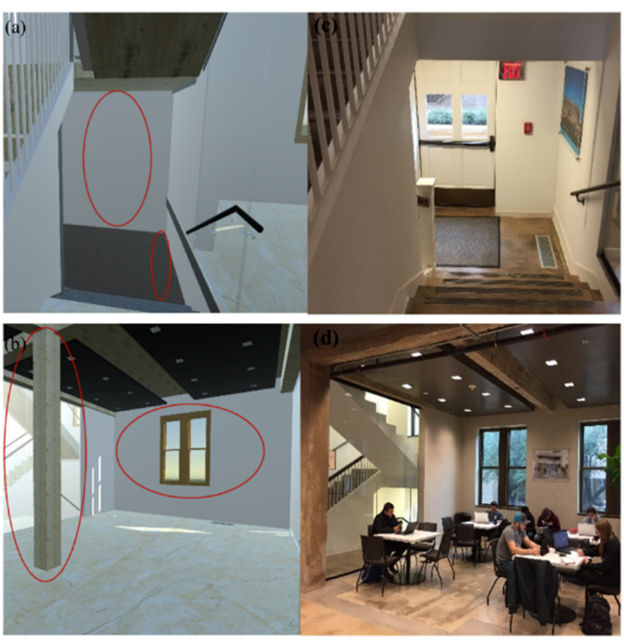

Fig. 4. The discrepancies between the models and the real building. (a) (b) Virtual model (c) (d) real building.

between 3D group and VR group (p = 0.787). This result suggests that advanced visualization technologies (3D and VR) facilitated participants' spatial memory development for the unfamiliar building. Fig. 6 shows the results of BIS in three groups. We further tested if this result was affected by gender. For males, we found a significant difference in building inspection task performance across the three groups ($p < 0.0001$, as shown in Fig. 7(a)). An all pairs-Tukey-Kramer HSD test found differences between 2D group and 3D group ($p < 0.0001$), and between 2D group and VR group ($p < 0.0001$). This result indicates that male participants in 3D and VR groups showed a better task performance than those in 2D group. In contrast, for females, we did not find any statistical differences in building inspection task performance across the three groups (p = 0.1395, as shown in the flowing Fig. 7(b)). This result may suggest that different visualization methods did not strongly affect females' spatial memory development. The performance difference across the three groups encouraged us to perform future analyses for explanations.

5.3. Relationship between review fixation time and spatial memory

Then we tested the relationship between review fixation time on the AOIs and the effectiveness of spatial memory development measured by BIS. According to the previous eye-tracking studies, fixation is defined as a stale eye-in-head position within two-degree dispersion tolerance over 100 to 200 ms staring duration and fixation time is defined as the cumulative duration of fixation within an area of interest [59]. It is a critical eye tracking metric that widely used in driving simulation [60,61], UI studies for web pages [62], and marketing [63]. Review fixation time represents participants' visual attention on each building component in this experiment.

An algorithm of calculating gaze fixation for each AOI was developed. Each AOI records the fixation time of each gaze visit in the array and calculates the aggregated gaze fixation time at the end of the experiment. The review fixation time is calculated by Eq. (1) as shown in Table 1. We first collected the gaze focus and navigation (walking trajectories in the 3D and virtual space) data in the review session. Fig. 8 visualizes participants' aggregated gaze movement and walking trajectories across the three groups. Fig. 8(a) shows the aggregated participants' gaze focus data in 2D group. It shows that participants paid much attention in the elevator and stairwell areas when reviewing a 2D drawing. Despite the fact that the participants were told that the elevator shall not be considered as an AOI before the experiment, they still spent a lot of time in that area as a reference (landmark) to memorize the general layout of the building. Fig. 8(b) shows the gaze and walking trajectory of participants from the 3D group. The red lines are participants' walking trajectories and purple to yellow dots are participants' gaze focus point clouds. Fig. 8(c) are aggregated the gaze and walking trajectories (red lines) of participants from the VR group.

Then based on the collected gaze and movement data, we calculated the review fixation time. Fig. 9 shows the distribution of review fixation time for all AOIs. The mean of the review fixation time was 4.54 s with a standard deviation of 5.73, and 90% of the review fixation time was less than < 11.86 s.

We analyzed the relationship between the review fixation time on each of the AOIs and the possibilities of correct discrepancy identifications. The Spearman correlation test indicates that there is a significant positive correlation between the review fixation time and the likelihood of finding the correct discrepancies, as shown in Fig. 10(a) (rho = 0.778, $p < 0.001$)). It indicates that as a participant spends longer time in reviewing a certain area, the likelihood of discovering something is wrong in the same area increases. Given that BIS is an indicator of the spatial memory development, it suggests that visual attention is a predictor of spatial memory development. This finding is also supported by existing cognitive science literature [11–13]. Thus, a regression model was fitted as follows:

$$M_{combined} = 0.000675t^2 + 0.03819t + 0.4514 \quad (1)$$

where $M_{combined}$ is the overall spatial memory indicator, t is the fixation time.

We then analyzed if the visual attention-spatial memory relationship was the same across the three groups. We found that although in general BIS performance improved as review fixation time increased, the increasing rates were different across the three groups, suggesting that the format of information affects the visual attention-spatial memory development relationship. Fig. 10(b) shows the relationships between fixation time and the likelihoods of finding the correction discrepancies in the three groups. The 2D group demonstrated the

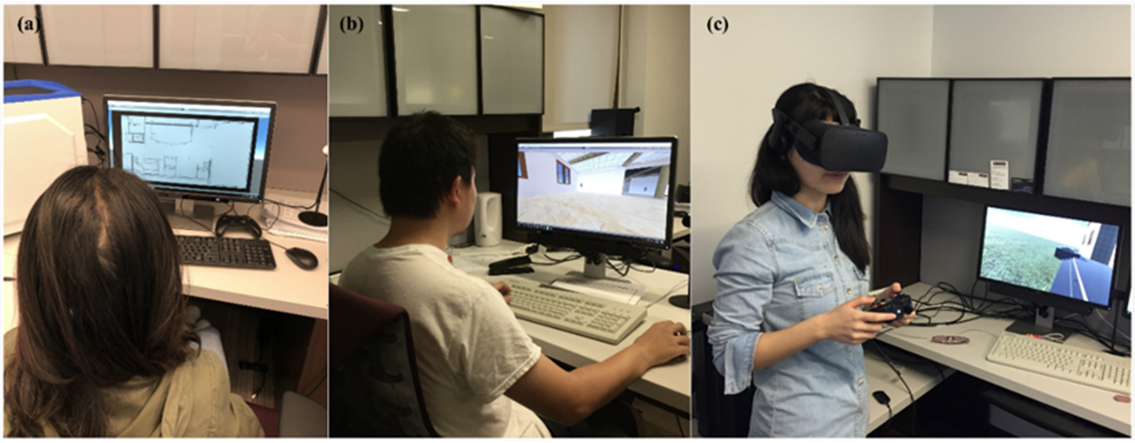

Fig. 5. The participants were utilizing the system to review the building (2D, 3D and VR groups respectively).

Table 3
Demographics of participants.

Demographic Factors	Response Range	Mean or Percentage	Median
Gender	Male/Female	55.56% male	–
Age	19–39	26.43	26
Degree level	Undergraduate/ Graduate	84.1% graduate student	–
Game experience	0–10	4.68	4
VR experience	0–10	2.79	2

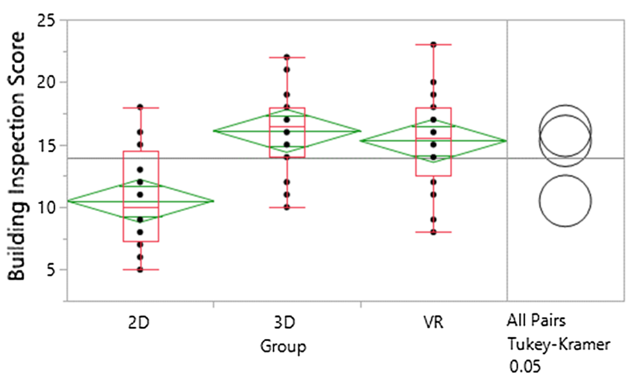

Fig. 6. The results of BIS across three groups.

lowest learning efficiency (measured as the increasing rate), indicating that prolonging review time with 2D drawings has the least impact on the development of better spatial memory. In contrast, the VR group showed the highest learning efficiency. As the review fixation time increased in the VR review, participants tended to develop a better spatial memory and the likelihood of finding the correct discrepancies was significantly increased. While the 3D group was somewhere between the 2D and VR groups. Based on the experiment data, three regression models were fitted for 2D, 3D and VR display respectively:

$$M_{2D} = -0.000217t^2 + 0.02171t + 0.416 \quad (2)$$

$$M_{3D} = -0.001655t^2 + 0.04143t + 0.5264 \quad (3)$$

$$M_{VR} = -0.005234t^2 + 0.08825t + 0.4726 \quad (4)$$

The difference existed across the three groups (Fig. 10b) suggests that a further analysis is needed to explain why the learning efficiency or increasing rate is affected by the visualization methods. Our first effort was to examine the effective attention ratio, i.e., the percentage of the aggregated attention time on all discrepancies versus total review time as shown in Table 1. Since the distributions of effective attention ratio passed the normality test (Shapiro-Wilk tests), we applied a one-way ANOVA test to compare the effective attention ratios across of the three groups ($\alpha = 0.05$) and found a significant difference ($p < 0.001$, see Fig. 11). Post hoc comparisons by Tukey-Kramer HSD testing also found significant differences between 2D group and 3D group ($p < 0.001$), between 2D group and VR group ($p < 0.001$), and between 3D group and VR group ($p = 0.006$). Specifically, participants in

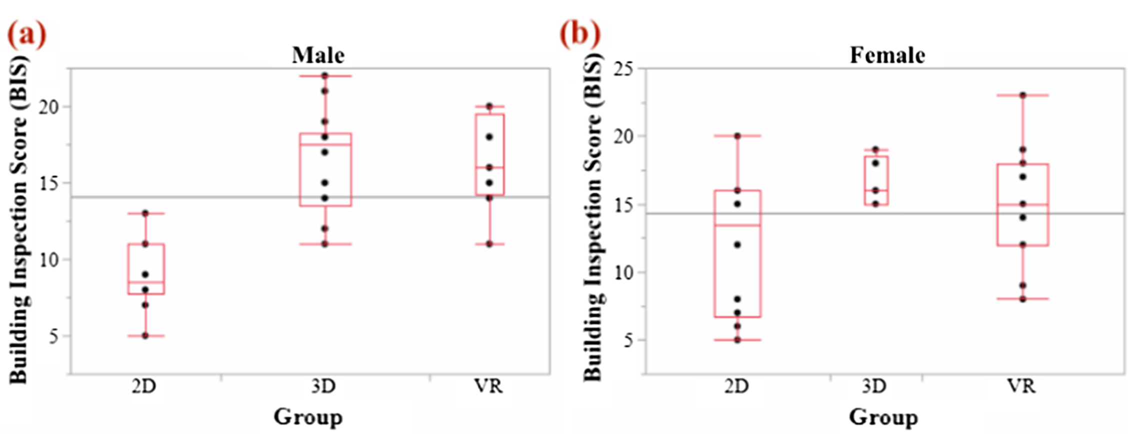

Fig. 7. The results of BIS across three groups by gender. (a) Male; (b) Female.

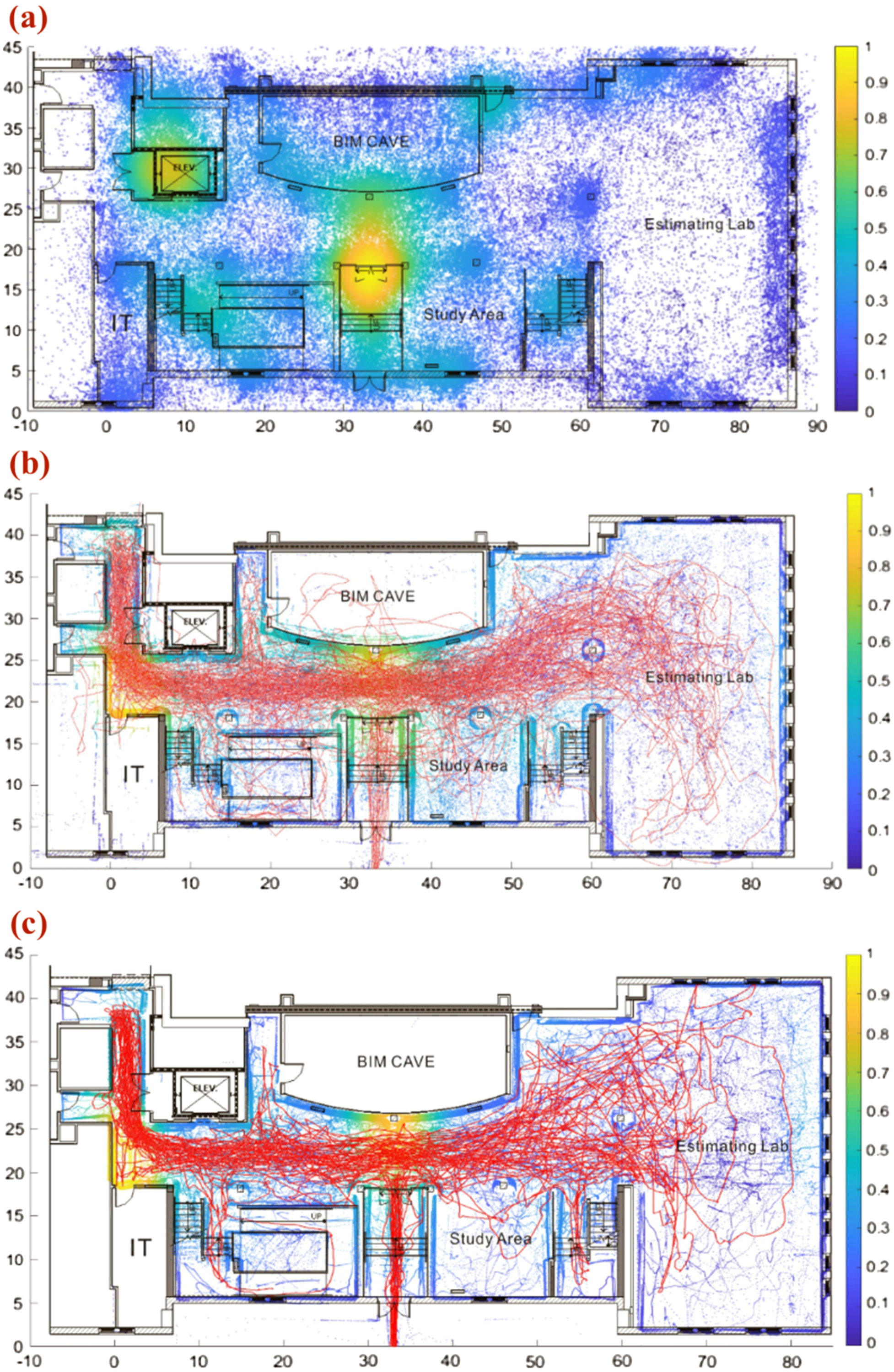

Fig. 8. Aggregated gaze and walking trajectories data of the three groups (2D, 3D, VR). (a) 2D group data; points refer to gaze focus points and colors indicate density. (b) 3D group data; points are gaze focuses and lines are walking trajectories. (c) VR group data; points are gaze focuses and lines are walking trajectories.

VR group paid more attention on AOIs than participants in other groups in the review session. Although all participants did not know what the discrepancies were when they were reviewing the models of the building, the results indicated that the VR helped participants concentrate on the details of important building components, and thus improved the overall performance. In general, the VR learning efficiency curve in Fig. 10(b) was higher than the other curves (and similarly for 3D curve versus 2D curve),. Following the cognitive science literature [30,33,38–42] claiming that spatial memory development can be affected by spatial knowledge acquisition strategies, we further investigated the spatial knowledge acquisition strategies used by the participants across the three groups.

5.4. *Spatial knowledge acquisition strategies as the mediating factor*

The traditional methods of assessing the acquisition strategies of

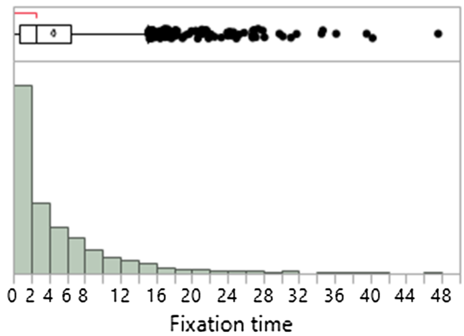

Fig. 9. The distribution of review fixation time

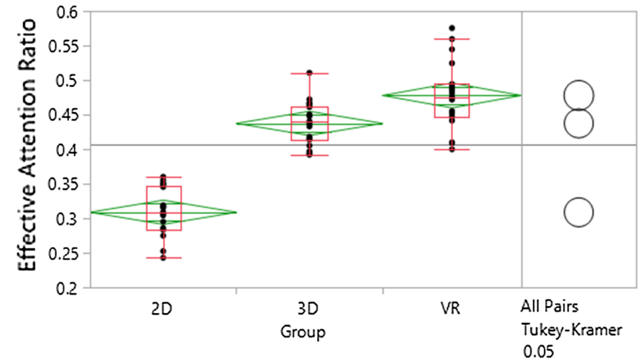

Fig. 11. Effective attention ratios across the three groups

spatial knowledge are to measure navigation distance and orientations [30,33,38,39], hand-draw sketch maps [40–42], and scales such as Santa Barbara Sense-of-Direction (SBSOD) [64]. Unlike traditional methods, this study focused on providing an alternative approach by using the eye-tracking to evaluate the acquisition of the spatial knowledge in real time [65]. It should be noted that we only focused on the landmark knowledge and route knowledge acquisition analysis in this study. The survey knowledge, i.e., the mentally abstract map-like representation of the built environment [14] will be in the future agenda of our research.

5.4.1. Landmark knowledge

Acquiring landmark knowledge is the first stage of developing spatial knowledge in the unfamiliar built environment. In this study, we surveyed participants in the post-experiment session about the main "anchoring points" they used in the review session to memorize the overall layout of the space. According to their feedback, three building components were selected as the main landmarks of the building, including stairwells on both sides and the elevator. The gaze fixation method was implemented to assess the effective attention ratio of the landmarks. Using gaze movement data to infer cognitive processes follows the *eye-mind* hypothesis in cognitive science literature, for example [65,66]. According to the Shapiro-Wilk tests, the effective attention ratios were normally distributed. Thus, one-way ANOVA test was implemented to evaluate if participants in the three groups spent similar amount of time for landmark knowledge acquisition. As

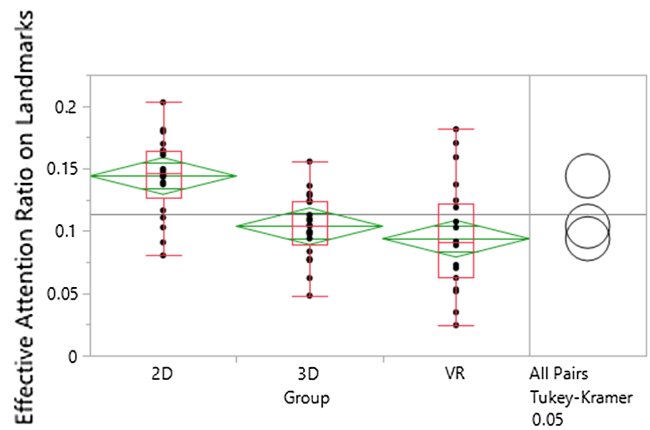

Fig. 12. The results of effective attention on the landmarks across three groups

illustrated in Fig. 12, the result indicates a significant difference ($p < 0.0001$) across the three groups. A post hoc comparisons for all pairs-Tukey-Kramer HSD test found that there were significant differences between 2D and 3D groups ($p < 0.0008$), and between 2D and VR groups ($p < 0.0001$). The difference between the 3D and VR groups was not significant though ($p = 0.6047$).The result indicates that participants in 2D group relied heavily on landmarks to acquire

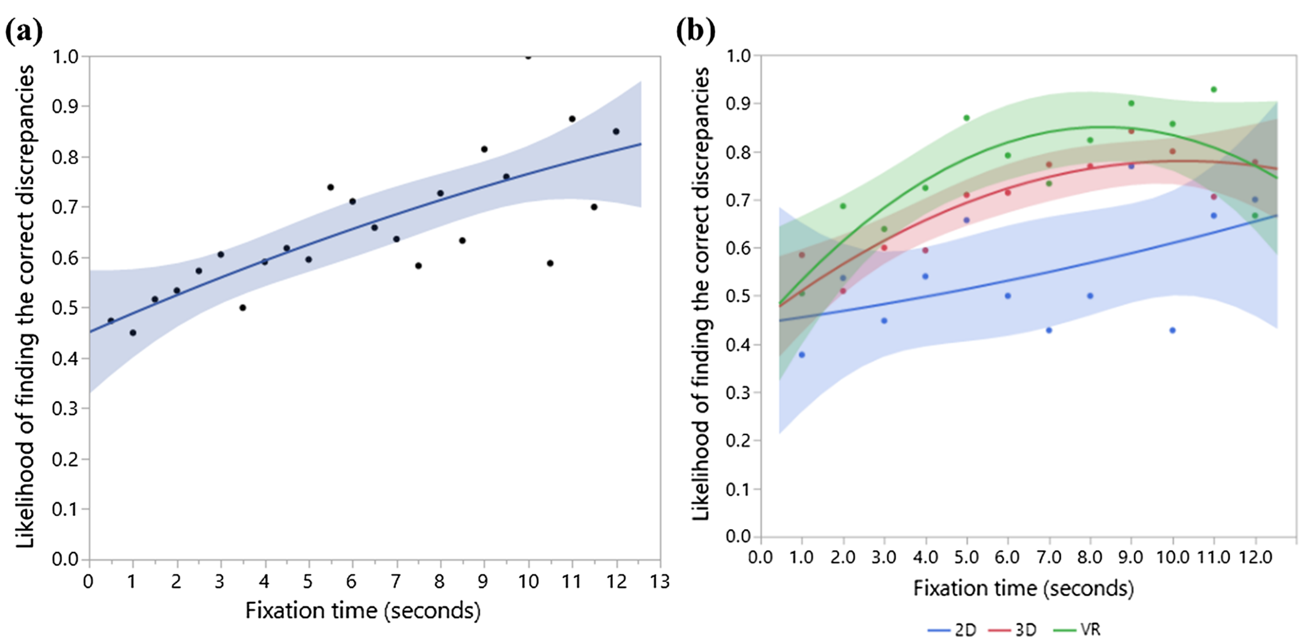

Fig. 10. (a) The relationship between review fixation time and likelihood of finding the correct discrepancies (b) The relationships across three groups

spatial knowledge about the building, and sequentially, developed their spatial memory. It was also supported by the post-experiment interview as most of them (16 out of 21 participants) confirmed that they selected some reference points (landmarks) on the 2D drawing to memorize the layout of the building. They specifically mentioned that they selected elevator and stairwells as their reference points (landmarks) since these building components were easy to identify on the drawing. In contrast, participants in 3D and VR groups reviewed and memorized the building in a participatory way. They paid less attention to these landmarks.

5.4.2. Route knowledge

Given the difficulty of a direct measurement of the cognitive process related to spatial information acquisition, literature has been using gaze tracking as an indirect indicator. According to Siegel and White [17]'s study, the route knowledge is encoded as the memory of the sequence of landmarks or turns. As a result, a more sequential and stable gaze movement in spatial information review may relate to the use of route knowledge. [67,68] further found that gaze transition entropy to be an effective indicator of visual attentions related to areas of interest (AOI). A higher value of gaze movement entropy indicates more irregularity and unpredictability of gaze movement, suggesting that participants just randomly look around in the environment. On the other hand, a lower value of gaze movement entropy shows the a more regular and relatively stable gaze focus transitions, indicating that the participants' gaze movement may have followed navigation and turns related to building the route knowledge. This is supported by Hartley, Maguire, Spiers and Burgess [69] finding that the eye movement is associated with the forward motion and turning during the navigation. Although we cannot conclude that distinct gaze movement patterns are results of different cognitive processes. But at least, we shall be able to claim that distinct gaze movement patterns, such as entropy of visual pathways, indicate the use of different spatial information acquisition methods. Therefore, we evaluated participants' route knowledge based on participants' gaze movement entropy in vertical and horizontal directions in this study. It shall be noted that the perception of the horizontal and vertical directions is not uniform, which deserves a further investigation that is out of the scope of this research. The basis of visual pathway entropy analysis is that when people develop their route knowledge during the review, their gaze movement trajectories should follow certain patterns in the vertical and horizontal directions such as turn left, turn right, bottom-up, or up-bottom. In other words, if the participants in the three groups (2D, 3D, VR) used different spatial knowledge acquisition strategies, participants' gaze movement data shall demonstrate different levels of regularity and predictability during review. A preliminary visualization suggests the existence of the gaze movement difference. Fig. 13 illustrates the first 10 s of gaze movement data of three participants from the three groups each. The lines represent participants' gaze movement. Fig. 13(a) shows that the participant from the 2D group had a more irregular and less predicted gaze movement when he/she was reviewing the building layout. In contrast, Fig. 13(b, c) indicate that participants from the 3D and VR groups demonstrated a more regular and predictable gaze movement. The Approximate Entropy (ApEn) was selected to evaluate the regularity and unpredictability of the fluctuations over participants' gaze movement data. ApEn is defined as a technique to quantify the regularity and complexity of the noisy time-series data [70]. This method is widely used in the data analysis of physiological time-series data such as heart rate [71,72], Electro-Encephalon-Gram(EEG) [73,74], and endocrine hormone [75,76]. According to Pincus [77]'s research, ApEn is calculated by the following algorithm. ApEn is calculated by the following algorithm, as shown in Table 4.

In this study, the higher value of ApEn indicates more irregularity and unpredictability of gaze movement, showing that the participants just randomly looked around in the building model during the review session, instead of attempting to develop the route knowledge about the space. The lower value of ApEn, in contrast, indicates that participant's gaze movement was relatively stable and regular, and the participants attempted to develop the route knowledge during the review of the building model. The ApEn of participant's gaze movement was calculated with MATLAB [78]. The ApEn of gaze movement data was analyzed in × and y directions. The z direction was not analyzed because participants did not move vertically in the experiment. For each participant, the × and y gaze trajectory data was separately processed by this algorithm. The ApEn in x-axis and y-axis in all three groups were found to be normally distributed based on the Shapiro-Wilk tests of normality. Thus, one-way ANOVA was used to compare the ApEn results across the three groups in × and y directions. For the ApEn in x-axis (horizontal direction), there was a significant difference ($p < 0.0001$) across the three groups. Specifically, a pairwise comparisons test for all pairs-Tukey-Kramer HSD test found differences between 2D and 3D groups ($p < 0.0001$), between 2D and VR groups ($p < 0.0001$), and between 3D and VR groups. Fig. 14 (a) shows the results of ApEn comparison results in x-axis. Similar differences were also found for the ApEn values in y-axis (vertical direction) ($p < 0.0001$). A pairs-Tukey-Kramer HSD test supported differences between the 2D and 3D groups ($p = 0.0002$), between 2D and VR groups ($p < 0.0001$), and between 3D and VR groups ($p < 0.0001$), as illustrated in Fig. 14 (b). The results of the ApEn comparisons in both × and y directions indicate that participants in the 2D group showed the most irregularity and unpredictability in terms of gaze movement patterns in both horizontal and vertical directions. They did not rely on the route method to acquire the spatial knowledge about the building. While the 3D and VR groups (especially the VR group), showed much more regularity and predictability in gaze movement, suggesting that route knowledge was gained when reviewing the model. Considering the findings of landmark knowledge assessment (5.3.1), we should be able to state that that participants in the 2D group leaned to landmark knowledge to develop their spatial memory, i.e., focusing more on scanning the 2D drawing and memorizing the relative locations of major landmarks in the building. These landmarks were later used as the "anchoring points" of their spatial memory in the inspection task. While participants in 3D and VR groups (especially the VR group), were able to develop enough route knowledge about the building and use the route knowledge more as the base of their spatial memory. The findings further suggest that different spatial knowledge acquisition strategies affected the development of spatial memory in the building inspection task at different levels. To be specific, landmark knowledge-based spatial memory development may be less effective than the route knowledge-based spatial memory development. This constitutes a possible explanation for why 2D group demonstrated the lowest learning efficiency (least increasing speed) in review fixation time – spatial memory performance relationship.

6. Discussion

The results of this study indicate that there is a general positive relationship between visual attention (measured as the review fixation time on the area of interest) and their spatial memory development in the building inspection task. Nonetheless, this positive relationship was different depending on the spatial information visualization methods in during the review of the engineering and design information. Specifically, the overall spatial memory development of the 3D and VR groups were better than the 2D groups. In addition, the three groups demonstrated different increasing rates in the visual attention-spatial memory relationship, suggesting that the learning efficiencies were different. We explored the possible explanation from two perspectives. (1) We investigated participants' effective attention ratios on the main AOIs. The results indicate that the participants in the VR group had the highest effective attention ratio, i.e., they paid more attention on the AOIs that directly contributed to the successful identification of discrepancies. Even though participants did not know what the discrepancies were when they were reviewing the drawing/model, VR

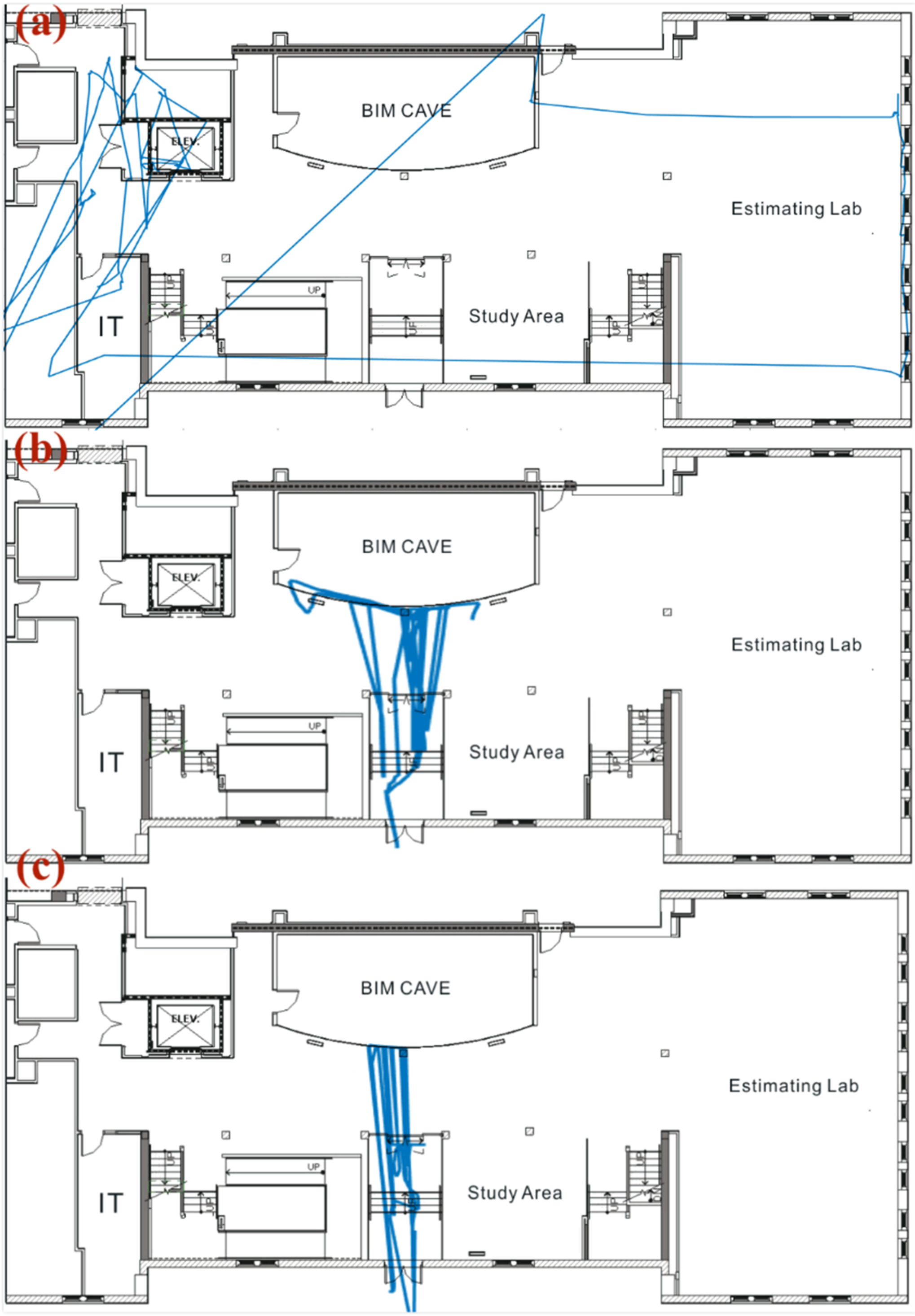

Fig. 13. The first 10 s of gaze movement data of three participants from the three groups each. (a) 2D group (b) 3D group (c) VR group

helped participants concentrate on details of key building components, which helped their spatial memory development later. In contrast, participants in the 2D group showed the lowest effective attention ratios, indicating that 2D drawing did not help them focus on details. This observation possibly explained why in general, VR and 3D groups showed a better spatial memory than the 2D group (2) we also examined the spatial knowledge acquisition strategies used by the three groups. Based on the holistic assessment of participants' gaze data including effective attention on landmarks and gaze movement ApEn, we found that participants in the 2D group showed a relatively higher concentration on major building landmarks (stairwells and elevator) compared to 3D and VR groups. This result suggests that participants in the 2D group tended to use more landmark knowledge in comparison with other teams as their spatial knowledge acquisition method to develop spatial memory. Participants in 3D and VR groups, in contrast, inclined to rely a little more on route knowledge as their main spatial knowledge acquisition method. To be noted, it does not mean that any group in this experiment relies only on a single spatial acquisition method; instead, it shows obvious allocation differences in their review attention. This could possibility be one of the driving factors of varying

Table 4
The algorithm of calculating ApEn for route knowledge assessment.

Approximate Entropy (ApEn) Algorithm [77]
Step 1:
*Define input parameters: N, m, and r. N is the length of the gaze raw data. m is the length of the compared runs, m = 2. r is effectively a filter. r = 0.2*std, std is the standard deviation of the gaze raw data.*
Step 2:
Given N data points [u(i)], from vector sequences x(1) through x(N-m + 1), defined by x(i) = [u(i),……,u(i + m-1)].
Step 3:
The distance between vector x(i) and x(j) is defined as d[x(i),x(j)] as the maximum difference in their respective scalar components.
Step 4:
For each i≤N-m + 1 in x(1),x(2),…..,x(N-m + 1),
Calculate $C_i^m(r)=$ *(number of j≤N-m + 1 such that d[x (i), x (j)]≤r)/(N-m + 1)*
$C_i^m(r)$ *is defined as a ratio that represents the number of vectors meet the maximum constraint under the length of the gaze raw data.*
Step 5:
Calculate $\phi^m(r) = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \ln C_i^m(r)$
$\phi^m(r)$ *is the aggregated calculated number of* $C_i^m(r)$ *under certain m and r condition.*
Step 6:
Calculate $ApEn = \phi^m(r) - \phi^{m+1}(r)$

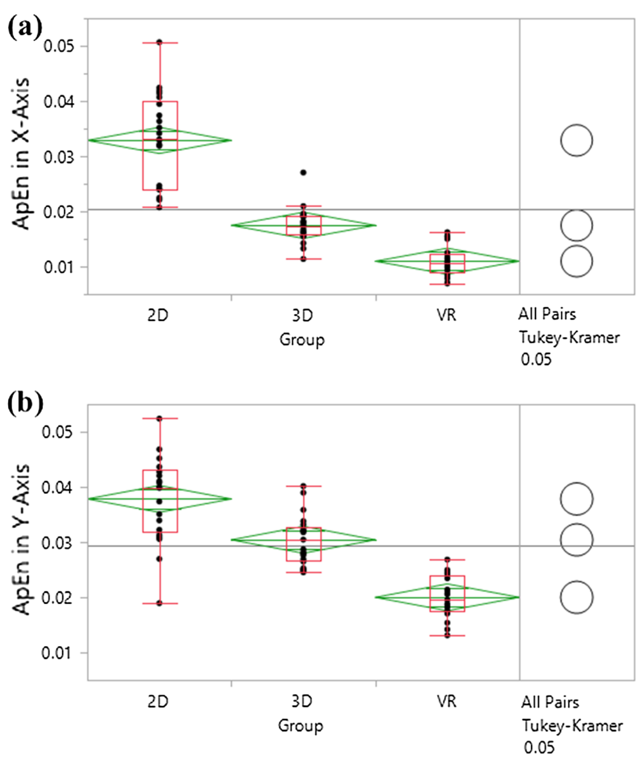

Fig. 14. The results of ApEn across different visual conditions. (a) x-axis (b) y-axis

increasing rates in the visual attention-spatial memory development relationship.

This study contributes to the AEC literature in the following ways: (1) the evidence about the positive relationship between visual attention (during the information review) and the spatial memory helps us identify a useful predictor of task performance that depends on the spatial memory. It will help AEC professionals to predict, and therefore to intervene, the performance of critical tasks, using handful eye-tracking measures in the pre-task review phase. This method will also help improve the performance and safety of other applications such as emergency response. For example, the prediction method will greatly help fire chefs to predict firefighters' spatial memory performance before they enter the unfamiliar sites. (2) This study also found evidence about the role of spatial knowledge acquisition strategies (affected by the information visualization methods) in the development of spatial memory, which helps explain the different AEC task performance using different engineering information formats observed in many studies. Amid the fast development of information visualization technologies, such as the use of BIM and VR/AR, researchers have tested if the emerging technologies could affect task performance. Participants in our study stated that the 3D and VR could provide a more realistic experience in the building (Mean = 7.4 on a scale of 0 to 10) and they were interested in using these visualization methods to review unfamiliar buildings in the future (Mean = 8.35 on a scale of 0 to 10). Representative studies, such as [22,23,79], have discovered the similar impacts of information formats on AEC task performance. This study moves a step further by providing a cognitive explanation to the observed difference. It suggests that the semantically richer information provided by the newer visualization technologies may help users build a better spatial knowledge (e.g., route knowledge versus landmark knowledge) facilitating the development of spatial memory at different levels. In real world projects, it will help the design of automation methods regarding engineering information review and visualization, to focus on triggering better spatial knowledge acquisition processes. Building on this study, researchers may be able to develop personalized information systems that tailors into the unique spatial cognitive processes of the end users. As an example, the authors have developed a personalized wayfinding information system for first responders [80]. (3) Although the implementation of eye-tracking technique is not novel in AEC research, this study provided a valuable research approach of using eye-tracking in different visualization conditions to evaluate user's task performance. This study also confirms the effectiveness of eye-tracking method in capturing the cognitive process (in terms of attention patterns) of people, and thus inspiring the innovative engineering information review system with eye-tracking functions. The eye tracking system we developed worked seamlessly with 2D, 3D and VR models of the building. It sets the foundation of the next generation engineering information systems that are intelligent and proactive.

Our study also presents opportunities for improvements. First, the accuracy of eye tracking still needs to be improved. Despite the accuracy of Tobii eye tracker 4C and Raycast technique, some participants mentioned that there were slight mismatches between captured gaze points and their real gaze points. Although these mismatches were minor and should not have affected the general conclusion of this study, for the possible cognitive prediction model as discussed earlier, a stronger eye tracking will guarantee the reliability. Second, this study has only focused on investigating how visual attention in information review affects spatial memory in a small-scale building. A large and complex building environment will induce cognitive overload [32] and may affect the findings of this study. Lastly, the survey knowledge was not analyzed in this study. A comprehensive study of spatial knowledge acquisition will be conducted in the future. The contribution of this research also lies on providing evidence about the impacts of visual attention on task performance in a practical design scenario. It helps expand the theoretical findings from the cognitive and perception science literature to a more realistic and practical setting. The findings of this research are expected to facilitate the cross-validation of basic perception research results and provide translational values.

7. Conclusions

This study investigates the relationship between visual attention and spatial memory development, which may be mediated by the strategies of spatial knowledge acquisition. A human-subject experiment was conducted to investigate the spatial memory development in a building inspection task based on a real building on Texas A&M University campus. Three information visualization methods were used in the review session including 2D drawing and 3D and VR models. The visual attention patterns and the building inspection task performance were used to analyze the roles of visual attention, and spatial knowledge acquisition, in forming the spatial memory that is directly related to the inspection performance. The results indicate a strong positive relationship between the visual attention and spatial memory. Furthermore, it also found that the spatial knowledge acquisition strategies play an important role in the increasing rate of the visual attention – spatial memory relationship. This study is expected to contribute to the construction information technology literature by providing evidence about a cognition-driven information system design that tailors into the spatial cognitive process of AEC professionals.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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