Investigating the Effects of Physical Landmarks on Spatial Memory for Information Visualisation in Augmented Reality

Jiazhou Liu* Monash University
Kadek Ananta Satriadi† Monash University
Barrett Ens‡ University of British Columbia
Tim Dwyer§ Monash University

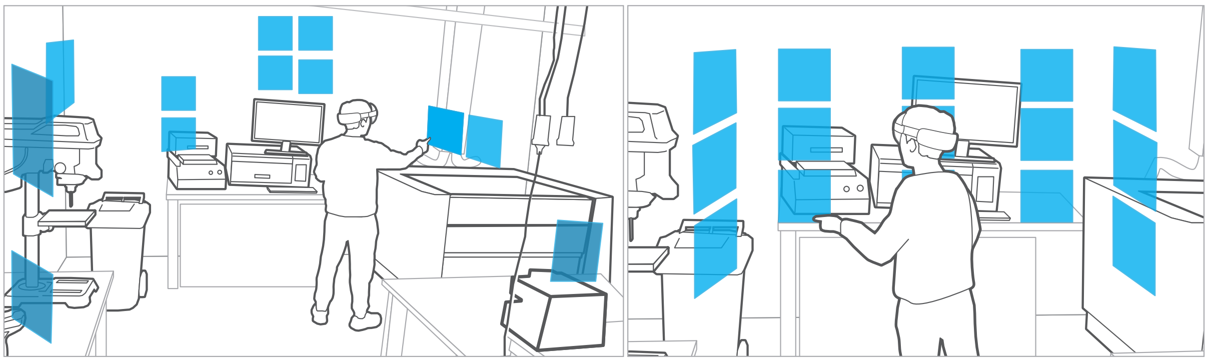


Figure 1: Two scenarios in which virtual views are overlaid on the physical environment: (left) Situated Analytics – data visualisations are displayed close to their spatial referents and (right) Small-multiples Visualisation with display layout decoupled from the environment – displaying views in an arbitrarily large display space around the user. The spatial relationships between physical landmarks and virtual targets may influence spatial memory when recalling the locations of these virtual targets.

Abstract

Augmented Reality (AR) is touted to be beneficial in supporting situated information display, allowing virtual information panels to be overlaid on real-world scenes. People must then use their spatial memory to navigate among these virtual panels effectively. While spatial memory has been studied in physical environments (wall displays) and virtual reality environments, there has been little research on how physical surroundings might affect memorisation of virtual content in a mixed environment like AR. Therefore, we provide the first AR study of spatial memory, comparing two different room settings with two different situated layouts of virtual targets on an abstract spatial memory task. We find that participants recall spatial patterns with greater accuracy and higher subjective ratings in a room with furniture compared to an empty room. Our findings lead to important design implications for mixed-reality user interfaces, particularly in information-rich applications like situated analytics and small-multiples information visualisation.

Index Terms: spatial memory, immersive analytics, view management, physical landmark, augmented reality, mixed reality

1 Introduction

Augmented Reality (AR) can enrich our physical workspaces (such as manufacturing workshops [24, 65, 72], warehouses [28, 49, 59], wet labs [25, 26, 30], and medical facilities [7, 20, 50]) with arbitrarily large workspaces for overlaying virtual imagery. Recent advances such as low-latency, wide-FoV, pass-through headsets, may help lead to increasing adoption of AR across a number of domains. The ability to bring information "out of the display" and integrate it into the world around us allows digital information to be viewed within the context of objects in the surrounding environment. However, realising these advantages will require interface designers to rethink how to harness spatial skills for exploring information.

Large virtual workspaces have long been touted as beneficial in supporting "space to think" [36], Small Multiples Comparison [39], and collaborative visualisation [9]. However, the efficiency of such applications is dependent on the user's ability to remember the locations of multiple views. Studies have shown that the spatial layout of virtual views can impact recall. For instance, earlier work has shown that the spatial layout of virtual panels on wall displays can benefit more from a spatial memory effect compared to virtual navigation through a small viewport [58]. Meanwhile, in Virtual Reality (VR), it has been shown that a wrap-around layout negatively affects the ability to recall view positions compared to a flat layout or semicircular layout [40].

In AR applications, the preferred layout of information views may be influenced by the surrounding environment. Primarily, physical features of the built environment and objects within it provide readily available landmarks that can be used to reinforce memory of spatial relationships. Visual landmarks have been shown to improve recall performance in desktop UIs as well as in VR [15, 17, 62]. Using a room-sized workspace with a sensemaking task in AR, Luo et al. [43] found that people tend to anchor clusters of virtual views near landmarks such as office furniture. Yet, it remains to be observed whether such spatial anchoring affects recall ability in AR workspaces.

With this paper we aim to contribute to a better understanding of the impacts of the presence of objects in the environment and the relative placement of virtual views to spatial memory. We describe a user study (in Section 3) that compares recall performance in an office-like environment filled with furniture (providing implicit landmarks) versus a similar empty environment. To determine how the allocentric spatial relationships between views and landmarks impacts performance, our study includes a second factor that compares furniture-aligned views with a regular, grid-like layout (see Figure 1).

*e-mail: liujiazhou@gmail.com
†e-mail: kadek.satriadi@monash.edu
‡e-mail: barrett.ens@ubc.ca
§e-mail: tim.dwyer@monash.edu

Our results (detailed in Section 3.6) show that participants were able to recall the positions of virtual views more accurately when physical landmarks were present. Subjective feedback indicates more positive ratings, better performance, less mental and physical effort, and less frustration with the room with physical landmarks than the empty room. While the layout factor did not impact performance, participants preferred a grid layout when furniture was not present. Overall, these findings suggest that anchoring virtual information views near physical landmarks, even without semantic relationships between the views and landmarks, improves people's ability to accurately recall the spatial positions of the views.

In summary, we present a contribution to the first rigorous study testing the effects of physical landmarks on spatial memory in an AR environment. From the discussion of our findings in Section 4, we infer a set of design guidelines for the layout of information views relative to the environment that supports spatial memory and navigation in situated and immersive visualisation scenarios.

2 Related Work

We review previous work on situated information displays using AR, focusing on the placement of virtual information panels. Next, we provide a brief introduction to spatial memory from the fields of both Psychology and Human-computer Interaction (HCI). Last, we discuss the effects of landmarks on spatial memory in 3D space.

2.1 Situated Information Displays

In an early investigation and prototyping of electronic field guide interfaces for biodiversity research, White et al. [66] proposed overlaying virtual botanical species identification results on a hand-held voucher via a video see-through display. They argued that the arrangement of the physical sample juxtaposed with virtual information affords better comparison. Recent research then has been exploring how situated information displays benefit immersive data visualisations and analytics. ElSayed et al. [11] introduced *Situated Analytics*, a technique that focuses on interactive visual analytics of data in its contextual environment. Their evaluation of shopping tasks suggested that situated analytics lead to better performance and higher user preference than traditional methods.

In the last decade, the HCI field has seen numerous situated AR applications and studies emerge [8, 13, 56]. For example, in the context of building maintenance, Prouzeau et al. [51] proposed "Corsican Twin", a user-centred design of AR situated visualisations using a novel authoring technique in VR to simulate operations and diagnose on-site equipment effectively. Ens et al. [12] presented a tabletop AR system that situates charts on tangible scale models. Such a prototype system is reported to be beneficial to collaborative knowledge-sharing and decision-making. Luo et al. [44] developed a situated visualisation system for human movement data analysis, enlightening future situated analytics workflows.

More recent work has established design spaces of situated information displays. Lee et al. [34] introduced design patterns derived from a systematic literature review of situated visualisation, while Satriadi et al. [54] proposed an extended model of situated visualisation that included local or hand-held miniature proxies of real-world referents. Researchers have also introduced design space exploration of how to place situated virtual views with the physical referents and techniques for layout management and optimisation [19, 18, 38]. For example, Satriadi et al. [55] presented six arrangement methods for virtual complex data representations around physical referents. Niyazov et al. [47] proposed user-driven constraints for augmented reality layout optimisation, allowing users to define and set up their own rules to place virtual information panels within the physical surrounding environments.

Recently, Luo et al. [43] studied how users prefer to place virtual views in fully-furnished AR workspaces during collaborative tasks. They observed participants tend to align virtual views near furniture. Yet, the benefits of such a strategy from the perspective of cognitive processes such as spatial memory remain unexplored. Thus, in this paper, we investigate the cognitive (i.e., spatial memory) effects of virtual views situated to physical objects (e.g., furniture) to support designing effective situated information displays.

2.2 Spatial Memory

Spatial memory allows people to collect and store information about their surrounding environment and facilitates navigation [46]. It plays a part in both short-term memory (i.e., working memory) and long-term memory (i.e., semantic and episodic memory) [3]. We focus on spatial memory representation in working memory, storing and processing information about the current environment.

Sholl's model for spatial memory [10, 57] explains the learning and retrieval of two spatial relations: egocentric spatial relations between the user and objects and allocentric spatial relations among the objects. Egocentric relations define a self-reference system, where self-to-object spatial relations are perceived in body-centred coordinates via the body axes. Allocentric relations describe an object-to-object system, encoding the spatial relations among objects in environmental coordinates, which can be formalised as a network of nodes interconnected by vectors. Recent work explored and evaluated Sholl's model and built several frameworks based on the model [6, 46, 64]. Moreover, when people learn a new environment, they interpret the spatial structure of the environment in terms of a spatial reference system [45], which influences spatial memory [61]. The Infocockpit system proposed by Tan et al. [60] provided large screens surrounding the user and ambient visual and auditory displays. The setup was found to improve spatial memory compared to desktop displays. These findings are essential to understanding how people perceive the surrounding environment regarding spatial memory from an egocentric perspective.

Researchers in HCI have since explored how spatial memory can improve user interface and task efficiency, especially in immersive environments such as VR [15, 31, 71]. Liu et al. [39] proposed a *shelf* metaphor to enhance spatial memory for small multiples visualisation in a VR environment. Han and Cho [21] tested flat, semi-circular, and full-circular user interaction techniques on spatial memory in VR and AR environments. They find that walking and grabbing support spatial memory. Liu et al. [40] evaluated the effects of flat, semi-circular, and full-circular display layouts on spatial memory in a VR environment. They found that flat layouts afford greater recall accuracy and more positive subjective ratings than full-circular layouts. They explained that the result may be impacted by different head rotations involved in different layouts.

In our study, we build upon Sholl's model to understand the effects of spatially directed motor activities, such as walking, hand reaching, and body/head rotation, on spatial memory in the self-reference system, as well as how spatial relations between physical landmarks and virtual targets are perceived in the object-to-object spatial reference system. While such effects have been explored in various VR studies listed above, it still remains unknown whether the implications of these studies still apply to a mixed environment such as AR. Thus, we investigate whether and how physical objects may influence spatial memory in AR.

2.3 Effects of Landmarks on Spatial Memory

To understand how landmarks influence spatial memory in 3D spaces, researchers have explored and evaluated various designs of artificial landmarks in virtual environments. In early work, Vinson [63] proposed a design guideline focused on using landmarks in human navigation in a virtual environment. They explain that landmarks indicate position and orientation and contribute to the development of spatial knowledge. Moreover, Bosco et al. [5] found an orientation specificity effect due to different spatial relations between target and landmarks. Uddin et al. [62] tested various artificial landmarks on spatial learning in a desktop environment and proposed that simple visual anchors have the potential to improve performance and spatial memory. Gao et al. [16, 17] further demonstrated that such landmarks assist multiple target learning and retrieval in VR. However, we cannot predict how these findings concerning landmarks in VR carry-over to the mixture of physical referent and overlaid information in AR scenarios. Therefore, we ask the same question of whether and how physical objects as environmental landmarks may influence the memorisation of locations of virtual information panels in AR.

3 User Study

In this section, we introduce our user study to investigate whether and how physical objects as landmarks influence the memorisation of locations of virtual information panels in AR. We first explain our design and hypotheses, followed by study tasks and procedures. Finally, we describe the outcome measurements for our study.

3.1 Design and Hypotheses

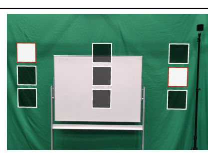
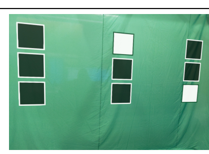
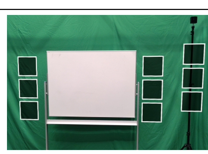
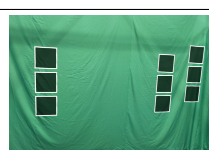
Mixed-reality scenarios overlaying virtual views on the physical environment involve three sets of objects that may influence spatial memory: the shape and extent of the *physical workspace* or environment; *physical landmarks* within the space; and virtual *information views* rendered by the AR system.

Physical Workspace—The size (or scale) and layout of the workspace are crucial considerations for spatial memory. We centre our research on office or workshop rooms designed with a standard rectangular layout. This choice is informed by insights gleaned from prior investigations [43, 40], which highlight the importance of facilitating efficient movement within such spaces [29]. By adopting this familiar structure, we ensure that our contributions seamlessly integrate with the existing body of literature.

Physical Landmarks—In the context of our study, landmarks are physical objects in the workspace. An office can contain multiple pieces of FURNITURE or electronic devices. To serve its purpose as a landmark, the object must have unique features. These features can be associated with the size relative to the surrounding objects, the complexity of the geometry, or perhaps unique experiences that one has with the objects.

Information Views—Situated information displays render charts, text, or application windows as virtual information panels. The quantity and dimensions of these views are adaptable, contingent upon the intricacy of the scenario under examination. Our primary emphasis lies in scenarios where users are required to interact with multiple views of a scale akin to standard application windows.

Thus, we design our study using a 2×2 (i.e. FURNITURE $\times$ LAYOUT) within-subjects design with four conditions as follows:

LAYOUT \ FURNITURE	*Furniture*	*NoFurniture*
Regular		
Irregular		

FURNITURE—True to our focus on office and workplace scenarios, we use common environmental landmarks for that setting, such as furniture and large electronic devices. The two levels are *Furniture* and *NoFurniture*. In the *Furniture* condition, eight unique items (see Section 3.3 for more details) are placed in fixed positions along the four sides of the room as environmental landmarks. Considering the size of the room (4 m $\times$ 4 m) and the size of the selected items, we evenly place two items along each side of the room. In the *NoFurniture* condition, landmark items are removed.

LAYOUT—We are also interested in exploring the effect of the spatial relationship between environmental landmarks and virtual views on spatial memory. We consider two configurations: *Regular*—virtual views are arranged in a grid unaligned to landmarks; and *Irregular*—virtual views are closely aligned with environmental landmarks. In the *Regular* LAYOUT condition, virtual views are displayed in a grid layout with fixed horizontal and vertical separation. In the *Irregular* LAYOUT condition, virtual views are placed close to furniture items.

These two factors result in four valid combinations: *Furniture-Regular*, *Furniture-Irregular*, *NoFurniture-Regular*, and *NoFurniture-Irregular*. Each participant experiences all four combinations, but the sequence is counterbalanced between each participant using a Latin square design.

Based on a pilot study (four participants), the results reported by related work, and our design rationale mentioned above, we preregistered [41] three hypotheses (italics):

H1 *If environmental landmarks affect users' spatial memory, participants will recall virtual patterns with environmental landmarks more accurately than without environmental landmarks.* We based this assumption on the preference for aligning virtual views with furniture observed in a study by Luo et al. [43], as well as in related works [15, 17] that landmarks support spatial memory.

H2 *If the alignment of environmental landmarks with the virtual views affects users' spatial memory, environmental landmarks closely aligned with views are more beneficial to users' spatial memory than weakly aligned landmarks.* We made this assumption according to the observed behaviours in the study by Luo et al. [43]. Thus, we may expect participants to rely more on the furniture as landmarks in the *Irregular* layout than the *Regular* grid layout.

H3 *Participants will answer the most quickly and feel the least mentally demanding in the condition that views are closely aligned with environmental landmarks among all conditions.*

3.2 Tasks

While past work in HCI exploring spatial memory adapts existing psychological models such as Data Mountain [29, 52] and Memory Palace [31, 69], the task stimuli vary among static figures [31], text or command [48], simple icons [15], and 2D map [27]. To avoid potential confounds introduced by the complex nature of such tasks, we follow Liu et al. [40] in adapting an abstract task developed by psychologists to assess visuo-spatial memory, namely the visual memory span task [42, 68]. In the visual memory span task, participants were presented with a grid pattern of squares (half filled with black and half with white) for a short duration. Such black-and-white patterns have no contextual and semantic relations with other objects in the same environments, ensuring participants focus on the spatial skills to memorise locations.

We use a total of 36 virtual target views arranged into twelve columns and three rows. The twelve columns are distributed evenly on four sides of the room, with three columns and three rows (nine) on each side of the room. To mitigate potential fatigue, we limit the study to a one-hour duration with a single task difficulty. Thus, in each task, participants must learn and recall the locations of five targets, following the same difficulty as the study design by Liu et al. [40]. The level of difficulty was also tested in our pilots (using 4–6 targets) and power analysis.

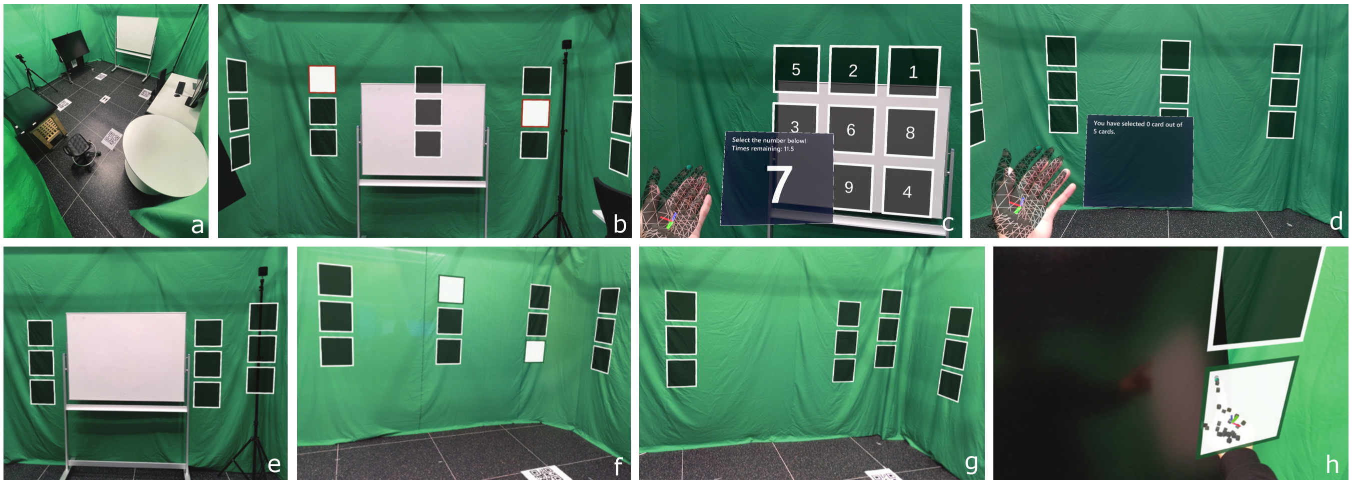


Figure 2: (a) A top-down view of the study room with furniture and electronic devices arranged around the edges. Examples of first-person view of study procedures under *Furniture-Regular*: (b) the *learning* phase; (c) the *distraction* phase; and (d) the *recall* phase. Examples of study room configurations under different conditions: (e) *Furniture-Irregular*; (f) *NoFurniture-Regular*; and (g) *NoFurniture-Irregular*. (h) Participants are asked to physically touch the virtual panels during the learning phase.

Each target is 0.3×0.3 m, with a vertical offset of 0.1 m between each pair (see Figure 2-b). On each side, the targets are displayed in a flat layout with a 1.5 m distance to the room centre. In the *Furniture* condition, the furniture or electronic devices are arranged slightly behind the cards to ensure that participants can reach them (e.g., a touch hand gesture to select a card as in Figure 2-h).

In the *Regular* condition, targets are displayed in a (3×3) grid layout on each side of the room with a horizontal offset of 0.5 m between each column and a height of 1.15 m for the lowest target (see Figure 2-b and f), while in the *Irregular* condition, each column is displayed closely aligned with the furniture or electronic devices, with a different column height either close to the top of the furniture (e.g., tabletop device or desk) or similar to the vertical centre of the furniture (e.g., tripod or whiteboard) (see Figure 2-e).

To reduce variability in the study data, we follow the same pattern generation method as the study by Liu et al. [40] via a constrained-random manner and validate the generations manually. The three constraints for the generations are: (1) no two adjacent targets can be included in the same pattern; (2) at least one target is included on each row to balance the pattern vertically; and (3) at least two targets are included on each side (left or right) to balance the pattern horizontally. The patterns used in our study can be found in the supplementary material.

Each trial is divided into five phases: *preparation*, *learning*, *distraction*, *recall*, and *rest*. In the *preparation* phase, participants are asked to stand at the starting position facing forward, as indicated by the footprint marks on the floor. Once in position, participants trigger the *learning* phase by pressing a virtual *Start* button. In the *learning* phase, a pattern of five white targets is revealed around the participants (Figure 2-b). Participants are given 15 seconds to tap each white target with either hand, causing the target boundary colour to change—the headset hand tracking must register five successful taps within the 15 seconds for the training to be valid.

Because short-term memory decays within 15–30 seconds [2], we include a *distraction* phase lasting at least 15 seconds between the learning and recall phases. In this phase, a distraction task requires participants to tap a new set of randomly numbered cards in a given sequence (Figure 2-c). Participants will see a countdown timer on top of the task board. During the distraction task, if participants have tapped the wrong cards or idled for five seconds, they will be penalised by adding five seconds to their current timer, with an upper of additional 15 seconds. Once the timer reaches 0, participants are automatically navigated to the *recall* phase.

In the *recall* phase, participants are asked to recreate the pattern shown in the learning phase by tapping on an empty layout. We do not set a time limit for this phase (Figure 2-d). Participants need to confirm their answers by tapping a button on the hand menu, which guides them to the *rest* phase.

In the *rest* phase, participants are asked to return to the starting position and get ready for the next trial. In this experiment, we do not show the results to participants because the results may stimulate participants negatively to develop different strategies for each trial. These phases are adapted from the work by Liu et al. [40].

The main interactions in this study are performed via mid-air gestures. We designed a hand menu 10.4×8.8 cm in size (see Figure 2-c and d) that can be toggled by showing or hiding the palm of either hand. We designed several buttons on the menu during the training and experiment. Participants can directly use one hand to touch the button on the menu while the other hand holds the menu. Participants can also touch the virtual targets directly.

3.3 Participants and Apparatus

We recruited 16 participants (eight female and eight male) aged between 21 and 39, all students or staff from our university. Of the participants, we measured the VR experience via a Likert scale ranging from 1 to 5. Five had little or no experience (self-rating 1–2), ten had at least some experience with VR ($2 <$ self-rating < 5), and one rated themselves as a VR expert (self-rating $= 5$). Participants signed up voluntarily and were rewarded a gift card ($20 AUD) as a sign of appreciation.

During the study, our participants wore a HoloLens 2[1] Augmented Reality (AR) headset. We developed a HoloLens Application using the Unity development environment (2020.3.43f1). We leveraged MRTK[2] for interactive components. The prototype ran directly on the HoloLens 2 device. The source code is publicly available and may be downloaded via GitHub: [37].

The experiment took place inside two physical rooms 4 m $\times$ 4 m in size. Participants needed to walk to navigate and were able to reach any point within the rooms. One of the rooms had eight unique pieces of furniture (including inactive electronic devices): a whiteboard (1.8 m height), a tall tripod supporting a motion camera (2.2 m height), a desk (0.8 m height) with an office chair under it and a monitor on top of it, a round table (1 m height), a movable

[1] Microsoft HoloLens 2: https://www.microsoft.com/en-us/hololens
[2] MRTK: https://www.mixedrealitytoolkit.org/

chair (0.5 m height), a tabletop device (1 m height), a tripod with a professional camera on top (1.5 m height), and a black Surface Hub (1.5 m height) (see Figure 2-a). The other room was empty, with all furniture and electronic devices removed. Both rooms had curtains from the roof to the ground to visually isolate them. The curtains were green to provide a strong contrast between the furniture, the AR visuals, and the background. For each room, there was a printed pair of footprints (A4 size) in the centre of the floor, indicating the participant's starting position and orientation. There were also four printed QR codes (A3 size) on the floor in each room to calibrate the AR headset to prevent location drifting.

3.4 Procedure

After completing a consent form and demographic questionnaire, participants were given a verbal explanation of the experimental setup and the trial workflow. Next, participants put on the Augmented Reality (AR) headset and performed a series of training scenes to gain familiarity with the study environment (i.e., walking around the study room), interactions with the stimuli (i.e., mid-air gestures), and the trial workflow (i.e., all phases with trial targets).

After the general training, participants completed four blocks of trials via the Latin square design, with each block containing six trials for one condition. In each block, participants first completed one practice trial, followed by five experimental trials. Then, participants were asked to remove the AR headset to take a short break between blocks. During the break, participants were asked to complete a short questionnaire with six questions adapted from the NASA-TLX [22] on a 7-point Likert scale. Following the completion of all 24 trials, participants completed a questionnaire with (1) the general strategy they used to complete the tasks, (2) whether and how the furniture helped them to memorise the patterns, and (3) ratings for the effect of four conditions on spatial memory. The total study duration was about 60 minutes, including roughly 30 minutes in AR. All participants completed the full set of trials successfully.

The experiment environment included green surrounding curtains, a marble floor, four A3 size calibration QR codes, a starting position sign, furniture described in Section 3.3 (only for the furniture conditions), and the experimental grid. The starting position, QR codes, furniture (only for the furniture conditions), and surrounding curtains were always visible during the experiment.

The vertical position of the grid was adjusted using a standard calibration for every participant at the start of the experiment. It was used to normalise the individual height differences and ensure that every participant had the same ability with the controls for selection. These configurations were adapted from Liu's work [39, 40] and validated through our pilot testing of different variations.

3.5 Measures

For each trial, we recorded the number of correctly chosen targets, along with their positions in the grid. We also recorded the time taken to select the five targets in the *recall* phase, i.e. *Recall Time*. The *Recall Time* was calculated from the start of each *recall* phase immediately after the timer of the distractor task ends to the time the participant pressed the button on the controller to indicate task completion. In our analysis, we used two methods to measure participants' recall accuracy: *Targets Incorrect* and *Euclidean Distance Error*. *Targets Incorrect* measures the number of targets selected incorrectly in each trial (also expressed as an open unit interval). To reveal deeper granularity in the responses, we further included the Euclidean Distance Error measure [29], which measures the sum of Euclidean distances (i.e., straight-line distances) from incorrectly selected targets to the correct targets. The Euclidean distance is a common distance metric for continuous space and has been applied more often to vectors that describe objects in a 3D space [29] than other distance measurements, such as a Manhattan distance [40]. Because the selection was non-sequential, there are many possible solutions to this measure, so we took the solution with the minimum distance as calculated using the Hungarian Algorithm [33].

Participants' head pose was tracked throughout each trial and was used to calculate the *Walking Distance* and *Head Rotations* in the learning phase. Subjective ratings and six questions adapted from the NASA-TLX [23] on a 7-point Likert scale for each of the four conditions were collected via online forms. The 7-point Likert scale adaptation from a 10-point scale has been used commonly in recent studies [35, 38, 40, 53] and is considered a more efficient yet still valid form of the original NASA-TLX [22]. In total, we collected data from 320 completed trials (16 participants × 2 FURNITURE conditions × 2 LAYOUT conditions × 5 repetitions). We treated the FURNITURE, LAYOUT as independent variables, as well as four combinations of these two variables. Dependent variables include accuracy, Euclidean distance error, recall time, walking distance, head rotations, NASA-TLX score, and subjective rating.

3.6 Results

Following APA recommendations [1], we report our analysis using estimation techniques with confidence intervals and effect sizes (i.e., not using p-values) following recent precedents in HCI [4, 67]. Our confidence intervals were computed using BCa bootstrapping, and the term *effect size* here refers to the measured difference of means. Error bars in our Figure 3 reporting means are computed using all data for a given condition. When comparing means, we average the data by groups and compare the conditions globally by computing the CI of the set of differences. A difference is considered significant when the CI of the difference does not cross 0. In our Figure 3, we display the computed CI of the differences. While we make use of estimation techniques, a p-value-approach reading of our results can be done by comparing our CIs spacing with common p-value spacing as shown by Krzywinski and Altman [32]. For the completeness of our analysis, we provide full inferential statistics in our supplementary materials.

Targets Incorrect—As shown in Figure 3-Target Incorrect (top), there is evidence that participants have fewer incorrect targets with the *Furniture* (0.43, CI [0.33, 0.53]) than with the *NoFurniture* (0.51, CI [0.41, 0.58]). This is also confirmed by our inferential statistics via an ART-ANOVA test ($F(1,47) = 4.71$, $p = 0.035$, effect size *partial* $\eta^2 = 0.09$). However, we can not find any difference between the two LAYOUT conditions, comparing *Regular* (0.44, CI [0.35, 0.53]) with *Irregular* (0.50, CI [0.40, 0.58]).

By analysing each condition combination, we find that participants have fewer incorrect targets with the *Furniture-Regular* (0.40, CI [0.28, 0.53]) than with the *NoFurniture-Irregular* (0.53, CI [0.39, 0.62]), as shown in Figure 3-Target Incorrect (bottom).

Euclidean Distance Error—We can not find any difference between the two FURNITURE conditions, comparing *Furniture* (2.00, CI [1.52, 2.51]) with the *NoFurniture* (2.36, CI [1.94, 2.73]). Also, we can not find any difference between the two LAYOUT conditions, comparing *Regular* (2.25, CI [1.77, 2.69]) with the *Irregular* (2.11, CI [1.67, 2.62]).

By analysing each condition combination, we can not find any difference between each pair of the condition combination.

Recall Time—We can not find any difference between the two FURNITURE conditions, comparing *Furniture* (2.00, CI [1.52, 2.51]) with the *NoFurniture* (2.36, CI [1.94, 2.73]). However, there is evidence that participants use less time to recall with the *Regular* (26.74, CI [25.28, 28.64]) than with the *Irregular* (29.59, CI [27.27, 32.61]), as shown in Figure 3-Recall Time (middle).

By analysing each condition combination, there is evidence that participants use less time to recall card patterns with the *NoFurniture-Regular* (25.82, CI [23.68, 28.91]) than with the *NoFurniture-Irregular* (29.96, CI [26.44, 34.68]) and the *Furniture-Irregular* (29.23, CI [26.24, 33.22]), as shown in Figure 3-Recall Time (bottom).

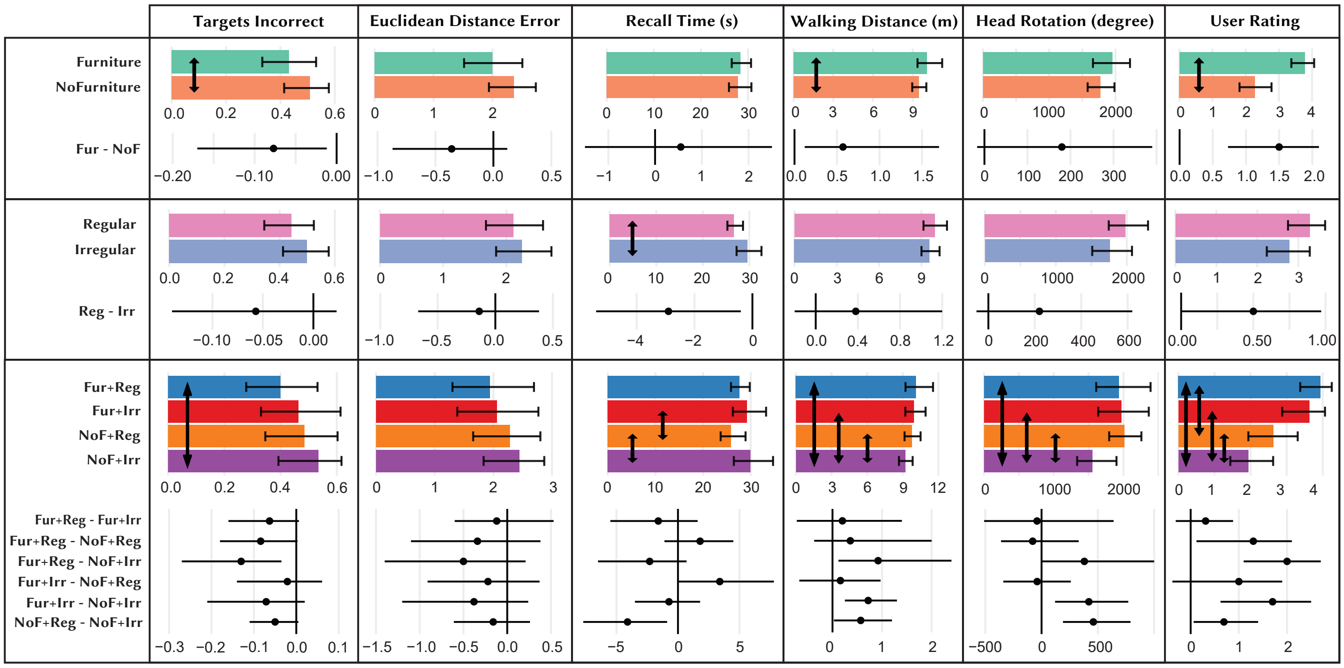


Figure 3: In each cell of each row (first row: each FURNITURE condition; second row: each LAYOUT condition; last row: each condition combination), the top chart shows means and CIs (error bar) for all measures for each grouped condition, while the bottom chart shows 95% CIs for the mean differences between grouped conditions. Arrows indicate significant differences between conditions.

Walking Distance—As shown in Figure 3-Walking Dist. (top), there is evidence that participants have more walking distance with the ■ *Furniture* (10.05, CI [9.36, 11.22]) than with the ■ *NoFurniture* (9.47, CI [8.96, 10.03]). However, we can not find any difference between the two LAYOUT conditions, comparing ■ *Regular* (9.94, CI [9.14, 10.80]) with ■ *Irregular* (9.56, CI [9.00, 10.28]).

By analysing each condition combination, there is evidence that participants have the least walking distance with the ■ *NoFurniture-Irregular* (9.20, CI [8.68, 9.83]) than with the ■ *Furniture-Regular* (10.12, CI [9.23, 11.55]), the ■ *Furniture-Irregular* (9.92, CI [9.21, 10.93]), and the ■ *NoFurniture-Regular* (9.20, CI [8.68, 9.83]), as shown in Figure 3-Walking Distance (bottom).

Head Rotation—We can not find any difference between the two FURNITURE conditions, comparing ■ *Furniture* (1953.08, CI [1660.53, 2219.87]) with the ■ *NoFurniture* (1771.85, CI [1580.45, 1985.48]). Also, we can not find any difference between the two LAYOUT conditions, comparing ■ *Regular* (1980.73, CI [1745.05, 2298.02]) with the ■ *Irregular* (1759.52, CI [1512.3, 2072.34]).

By analysing each condition combination, there is evidence that participants have the least head rotations with the ■ *NoFurniture-Irregular* (1551.81, CI [1335.85, 1900.35]) than with the ■ *Furniture-Regular* (1931.53, CI [1609.09, 2389.00]), the ■ *Furniture-Irregular* (1971.07, CI [1638.52, 2363.43]), and the ■ *NoFurniture-Regular* (2010.21, CI [1795.38, 2257.22]), as shown in Figure 3-Head Rotation (bottom).

Subjective Rating—As shown in Figure 3-Rating (top), there is evidence that participants rate a higher score for the ■ *Furniture* (3.78, CI [3.38, 4.06]) than for the ■ *NoFurniture* (2.28, CI [1.81, 2.78]). This is also confirmed by our inferential statistics via an ART-ANOVA test ($F(1,45) = 20.22$, $p = 4.81 \times 10^{-5}$, effect size *partial* $\eta^2 = 0.31$). However, we can not find any difference between the two LAYOUT conditions, comparing ■ *Regular* (3.28, CI [2.75, 3.66]) with ■ *Irregular* (2.78, CI [2.23, 3.28]).

By analysing each condition combination, there is evidence that participants rate a higher score for the ■ *Furniture-Regular* (3.94, CI [3.38, 4.25]) than for the ■ *NoFurniture-Regular* (2.63, CI [1.94, 3.31]) and the ■ *NoFurniture-Irregular* (1.94, CI [1.44, 2.63]). Also, participants rate a higher score for the ■ *Furniture-Irregular* (3.63, CI [2.88, 4.06]) and the ■ *NoFurniture-Regular* (2.63, CI [1.94, 3.31]) than for the ■ *NoFurniture-Irregular* (1.94, CI [1.44, 2.63]), as shown in Figure 3-Rating (bottom).

In the post-experiment questionnaire, we ask participants "*Did the furniture help you to learn and recall the patterns?*". Thirteen out of 16 participants answered "*Yes, the furniture did help*", while the other three participants answered "*No, the furniture did not help*". For the participants who rate furniture as helpful, we ask further questions: "*In which phase did you use furniture to memorise the patterns?*". Ten out of 13 participants answered "*Both learning phase and recall phase*", while the other three participants answered "*Learning phase*". We also asked "*How often did you use furniture to learn and recall patterns?*". Participants answered an average of 4.54 on a Likert scale from 1 to 5.

NASA-TLX Result—Figure 4 (top row) shows our CI analysis on FURNITURE factor. From the charts, we can see clear evidence that participants experience less Mental Demand (4.13, CI [3.48, 4.66] vs 5.19, CI [4.59, 5.71]), Physical Demand (3.94, CI [3.34, 4.5] vs 4.56, CI [3.97, 5.09]), Effort (4.34, CI [3.72, 4.91] vs 4.97, CI [4.24, 5.47]), and Frustration (3.19, CI [2.66, 3.76] vs 3.84, CI [3.13, 4.41]) but better Performance (4.19, CI [3.64, 4.75] vs 5.13, CI [4.59, 5.53]), with an average lower workload (4.12, CI [3.58, 4.53] vs 4.83, CI [4.36, 5.19]) with the ■ *Furniture* than with the ■ *NoFurniture*. This is also confirmed by our inferential statistics via ART-ANOVA tests.

Then, Figure 4 (middle row) shows our CI analysis on LAYOUT factor. From the charts, we find evidence that participants experience less Physical Demand (4.03, CI [3.44, 4.60] vs 4.47, CI [3.81, 4.94]) and Effort (4.47, CI [3.75, 4.97] vs 4.84, CI [4.16, 5.38]) with the ■ *Regular* than with the ■ *Irregular*.

Last, Figure 4 (bottom row) shows our CI analysis among all condition combinations. From the charts, we can see that the ■ *Furniture-Regular* achieves better TLX scores than the ■ *NoFurniture-Regular* with less Mental Demand (4.00, CI [3.09, 4.81] vs 5.13, CI [4.19, 5.81]) and better Performance (4.06, CI [3.31, 4.81] vs 5.13, CI [4.44, 5.63]), and an average lower work-

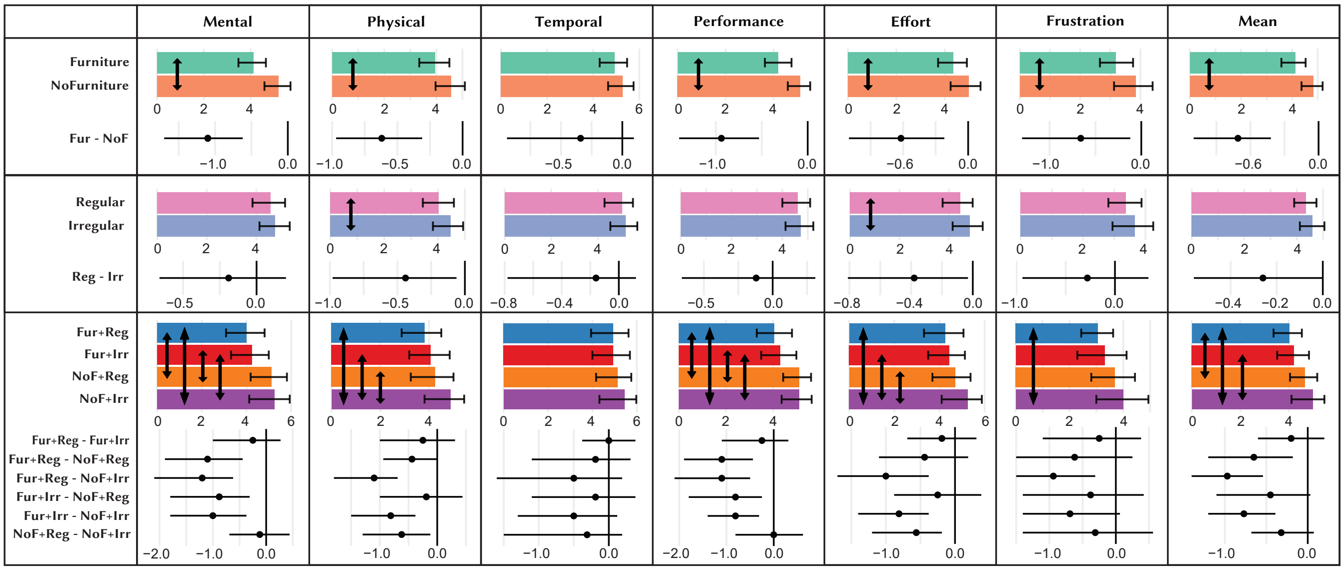


Figure 4: In each cell of each row (first row: each FURNITURE condition; second row: each LAYOUT condition; last row: each condition combination), the top chart shows means and CIs (error bar) for all NASA-TLX criteria for each grouped condition, while the bottom chart shows 95% CIs for the mean differences between grouped conditions. In the NASA-TLX, performance was rated in reverse order (lower is better). Arrows indicate significant differences between conditions.

load (4.02, CI [3.38, 4.54] vs 4.67, CI [4.05, 5.18]). Also, we find the *Furniture-Regular* achieves better TLX scores than the *NoFurniture-Irregular* with less Mental Demand (4.00, CI [3.09, 4.81] vs 5.25, CI [4.13, 5.94]), Physical Demand (3.81, CI [2.88, 4.50] vs 4.88, CI [3.81, 5.44]), Effort (4.25, CI [3.31, 5.06] vs 5.25, CI [4.10, 5.88]), and Frustration (3.06, CI [2.44, 3.63] vs 4, CI [3.00, 4.94]), but better Performance (4.06, CI [3.31, 4.81] vs 5.13, CI [4.37, 5.65]), with an average lower workload (4.02, CI [3.38, 4.54] vs 4.99, CI [4.11, 5.47]). In addition, we see the *Furniture-Irregular* achieves better TLX scores than the *NoFurniture-Regular* with less Mental Demand (4.25, CI [3.31, 5.00] vs 5.13, CI [4.19, 5.81]) but better Performance (4.31, CI [3.50, 5.00] vs 5.13, CI [4.44, 5.63]). Moreover, we find the *Furniture-Irregular* achieves better TLX scores than the *NoFurniture-Irregular* with less Mental Demand (4.25, CI [3.31, 5.00] vs 5.25, CI [4.13, 5.94]), Physical Demand (4.06, CI [3.19, 4.84] vs 4.88, CI [3.81, 5.44]), and Effort (4.44, CI [3.50, 5.13] vs 5.25, CI [4.10, 5.88]), but better Performance (4.31, CI [3.50, 5.00] vs 5.13, CI [4.37, 5.65]), with an average lower workload (4.22, CI [3.52, 4.84] vs 4.99, CI [4.11, 5.47]). Last, we find the *NoFurniture-Regular* achieves better TLX scores than the *NoFurniture-Irregular* with less Physical Demand (4.25, CI [3.25, 5.00] vs 4.88, CI [3.81, 5.44]) and Effort (4.69, CI [3.69, 5.38] vs 5.25, CI [4.10, 5.88]).

4 DISCUSSION

In this section, we discuss the results of our user study in the context of immersive view management. We structure our discussion based on our study conditions, design implications, and limitations.

4.1 Furniture Benefit Spatial Memory

Overall, we confirm our hypothesis **H1** from the quantitative analysis of both the accuracy results, subjective rating, and NASA-TLX scores. This finding supports the application of the well-known mnemonic technique, Method of Loci, in a situated Augmented Reality environment and aligns with the findings in VR [69] and physical environments [48].

Our accuracy results suggest that *Furniture* as landmarks lead to better user performance than no landmark in an empty room. Participants made fewer errors in the room with furniture than in the empty study room, as measured by *Targets Incorrect*. Although we can see the trend in the other accuracy measure, the analysis of the mean difference does not show clear evidence.

It is interesting to see that participants in the learning phase perform more walking distance in a room with furniture than in an empty room, as measured by *Walking Distance*. This finding aligns with the locomotion effect on spatial memory [29] that locomotion may positively benefit spatial memory. It is also possible that participants intentionally move to specific locations relevant to each piece of furniture to explicitly learn card patterns associated with the furniture (e.g., standing in front of the whiteboard helps participants recall the positions of the cards near the whiteboard).

From the results of subjective ratings and NASA-TLX scores, we can see overwhelming positive feedback that furniture helps participants memorise virtual patterns. Specifically, participants reported less mental and physical effort, less frustration, and better performance while working on the abstract task for spatial memory in a room with furniture than in an empty room.

Comments from 13 participants further explain this finding. For example, "*I tried to remember the location in relation to furniture, e.g., corner of TV or top of chair*" (P1), "*I used furniture to remember the pattern and use the top, middle, bottom to distinguish the row*" (P3), and "*To memorise which furniture is related to the patterns*" (P8). Participants also mentioned interesting strategies, such as using storytelling to associate the patterns with the physical objects, as mentioned by P2: "*I have to take the pencil and write on the whiteboard then put the pencil on the table and sit on the chair*".

Three participants who rated furniture as not useful reported different strategies for the task. Two of them used a directional mnemonic for each side of the panels (e.g., top-left, etc.), while one participant used a numerical mnemonic for each side of the panels (e.g., 1–9). The former strategy can be explained using Sholl's model, where participants remember patterns based mainly on egocentric relations. Participants using these strategies show better accuracy (*mean* $= 0.78$, *SD* $= 0.24$) than those who reported using furniture as landmarks (*mean* $= 0.47$, *SD* $= 0.18$) in our study. However, due to a limited sample size, we cannot conclude that the perception of egocentric relations benefits spatial memory more than working with allocentric relations.

4.2 The Influence of Display Layout and Furniture

We did not find conclusive evidence for the effects of situated layouts (i.e., views closely aligned with landmarks) from all the measures, and therefore hypothesis **H2** is not supported. It is interesting to see that participants spend less time recalling the pattern in the *Regular* condition than in the *Irregular* condition. This implies that a regular grid layout of virtual views may help users quickly locate the target view. Moreover, the NASA-TLX scores show that a regular grid layout affords less physical effort than an irregular layout. This can be explained by the fact that each row of the virtual targets is located at the same vertical height, requiring simpler physical movement from participants.

Regarding our hypothesis **H3**, although we found evidence that *Furniture-Irregular* affords less Mental Demand than *NoFurniture-Regular* and *NoFurniture-Irregular*, there is no clear evidence that *Furniture-Irregular* outperforms among all conditions in Recall Time and Mental Effort, which rejects our **H3**.

Our results also reveal some interesting findings. First, although *NoFurniture-Irregular* supports the least accuracy, especially a strong difference between *NoFurniture-Irregular* and *Furniture-Regular*, *NoFurniture-Irregular* affords the least walking distance and head rotation, supported by the strong evidence from our CI analysis. This may be explained by the fact that participants are reluctant to move and rotate to memorise the target positions in an empty room with all targets randomly placed, and thus affecting their accuracy. Second, participants in the *NoFurniture-Regular* condition spend less time recalling the positions of card patterns than in the *Furniture-Irregular* and the *NoFurniture-Irregular*. This may again imply that a regular grid layout in an empty room may help users quickly locate the target views.

Moreover, subjective ratings and NASA-TLX results show that participants prefer the *Furniture-Regular* condition and *Furniture-Irregular* more than the *NoFurniture-Irregular* condition and report higher mental and physical effort for the *NoFurniture-Irregular* condition. This may be due to the strategies that most participants used in the *NoFurniture* conditions, such as "*remembering the patterns from a 3 $\times$ 3 matrix on each wall*" (P9). This strategy does not work well in an *Irregular* layout where such a matrix can not be perceived easily. Interestingly, this subjective perception does not influence participants' performance much, which means that participants are able to perform well in an empty room with randomly placed views but perceive high physical and mental demands to compensate for the accuracy.

4.3 Design Implications

Based on our results and discussion above, we propose several design implications for guiding future designs of mixed-reality user interfaces and view management.

(1) An interesting design implication from our results is that working in a completely decluttered mixed-reality environment may not be necessary and not even particularly beneficial. In fact, **physical furniture is useful in providing landmarks** to enhance mind-map creation for the workspace (similar to the method of Loci) and could increase the efficiency of information retrieval for sensemaking tasks (e.g., [43]) and browsing tasks (e.g., [15]).

(2) With the new generation of video pass-through AR headsets (Meta Quest 3, Apple Vision Pro), developers can choose to completely block out the environment, for example, to hide furniture to focus on the visualisation panels. However, our findings suggest that **hiding furniture could compromise spatial memory**.

(3) When working in an empty room, i.e. a space without such physical landmarks, **adding virtual spatial referents** (e.g., virtual grids or shelves [39]) to virtual views **may enhance navigation** among virtual views.

(4) Another way to increase productivity in an empty room is to **display virtual views in several 3 $\times$ 3 grid layouts**. As our participants (P3, P9, P12, and P15) explained, such layouts would afford directional aid (e.g., top, middle, bottom, etc.) or numerical aid (e.g., number 1-9) to **help them recall the position of information views** using a mnemonic device rather than relative spatial position.

(5) Future mixed-reality user interfaces should **consider locomotion or direct interaction as design opportunities**. P14 mentioned in the post-study questionnaire that "*when my movement is significant, or returning to the centre each time I touch the square, it will help increase my spatial memory*". P6 also proposed a similar strategy to dramatically use the body gestures and movements so that the unconscious mental replay will enhance spatial memory. These findings align with the literature about the effects of kinesthetic cues on spatial memory (e.g., [14, 29, 70]).

4.4 Limitations and Future Work

Our study does not evaluate different workspace scales, which have implications on locomotion [29], landmark density, and information view density, any of which may influence spatial memory. Also, in our study, there is no semantic relationship between views and landmarks. This was to avoid potential confounds and cover as many scenarios as possible. However, the context would likely have semantic relationships with the display in realistic situated analytics scenarios. Last, the limited Field-of-View (FoV) of HoloLens 2 may hinder participant's ability to connect information views with physical landmarks. Participants reported that virtual content was only displayed on half of the vertical height of their FoV.

There are, of course, several more factors that should be taken into account in future studies. For example, P14 suggests that the furniture as landmarks is more useful when the virtual panel is to the top of furniture, such as to the top of tables and desks, than when it is to the left or right of the furniture. Thus, further studies could elaborate on the effects of relative positions between the information views and physical landmarks on spatial memory, such as comparing placing visual panels closer to physical landmarks with placing panels in empty spaces or even fully randomised positions. Moreover, the cardinality of this study is designed as one to three or six, where each physical landmark is mapped to three or six information views. Future studies could help to test the different cardinality configurations, such as a one-to-one mapping.

5 Conclusion

In this study, we examine how physical objects in the environment affect people's spatial memory via an abstract task in Augmented Reality, comparing two different room settings with two different situated layouts of virtual information panels. The results show that participants perform better in a room with physical furniture as landmarks than in an empty room. Moreover, from the subjective results, participants report less mental and physical effort, less frustration, and better performance while working on the abstract task for spatial memory in a room with furniture than in an empty room. This general result held regardless of the subordinate factor (i.e., situated layout) that we introduced, implying that the main factor that influences the performance is the existence of physical landmarks. In other words, physical landmarks benefit people's spatial ability to recall the positions of virtual information views in an Augmented Reality environment.

Our study design is the first to test spatial memory for immersive information displays in a room-sized AR environment and has important implications for the design of situated analytics and small-multiple display visualisation applications in AR, which we expect will become much more commonplace with improved AR technology. We hope this paper will establish a connection between spatial memory and situated analytic tasks in information visualisations, and inform future designs of mixed-reality user interfaces.

References

[1] A. P. Association. *Publication Manual of the American Psychological Association*. American Psychological Association (APA), 2009. 5

[2] R. Atkinson and R. Shiffrin. Human memory: A proposed system and its control processes. In *Psychology of Learning and Motivation*, volume 2, pages 89–195. Academic Press, 1968. 4

[3] A. D. Baddeley and G. Hitch. Working memory. In G. H. Bower, editor, *Psychology of Learning and Motivation*, volume 8 of *Psychology of Learning and Motivation*, pages 47–89. Academic Press, 1974. 2

[4] L. Besançon, M. Ammi, and T. Isenberg. Pressure-based gain factor control for mobile 3D interaction using locally-coupled devices. In *Proc. CHI*, CHI '17, pages 1831–1842, NY, USA, 2017. ACM. 5

[5] A. Bosco, L. Picucci, A. O. Caffo, G. E. Lancioni, and V. Gyselinck. Assessing human reorientation ability inside virtual reality environments: The effects of retention interval and landmark characteristics. *Cognitive processing*, 9:299–309, 2008. 2

[6] N. Burgess. Spatial memory: How egocentric and allocentric combine. *Trends in cognitive sciences*, 10(12):551–557, 2006. 2

[7] T. Collins, D. Pizarro, S. Gasparini, N. Bourdel, P. Chauvet, M. Canis, L. Calvet, and A. Bartoli. Augmented reality guided laparoscopic surgery of the uterus. *Medical Imaging*, 40(1):371–380, 2021. 1

[8] M. Cordeil, B. Bach, A. Cunningham, B. Montoya, R. T. Smith, B. H. Thomas, and T. Dwyer. Embodied axes: Tangible, actuated interaction for 3D augmented reality data spaces. In *Proc. CHI*. ACM, 2020. 2

[9] M. Cordeil, T. Dwyer, K. Klein, B. Laha, K. Marriott, and B. H. Thomas. Immersive collaborative analysis of network connectivity: Cave-style or head-mounted display? *IEEE TVCG*, 23(1):441–450, 2016. 1

[10] R. D. Easton and M. J. Sholl. Object-array structure, frames of reference, and retrieval of spatial knowledge. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 21(2):483, 1995. 2

[11] N. A. ElSayed, B. H. Thomas, K. Marriott, J. Piantadosi, and R. T. Smith. Situated analytics: Demonstrating immersive analytical tools with augmented reality. *Visual Languages Computing*, 36:13–23, 2016. 2

[12] B. Ens, S. Goodwin, A. Prouzeau, F. Anderson, F. Y. Wang, S. Gratzl, Z. Lucarelli, B. Moyle, J. Smiley, and T. Dwyer. Uplift: A tangible and immersive tabletop system for casual collaborative visual analytics. *IEEE TVCG*, 27(2):1193–1203, 2021. 2

[13] P. Fleck, A. S. Calepso, S. Hubenschmid, M. Sedlmair, and D. Schmalstieg. Ragrug: A toolkit for situated analytics. *IEEE TVCG*, 29(7), 2023. 2

[14] T. Friedrich, A. Prouzeau, and M. McGuffin. The effect of increased body motion in virtual reality on a placement-retrieval task. In *Proc. VRST*, VRST '21, New York, NY, USA, 2021. ACM. 8

[15] B. Gao, Z. Chen, X. Chen, H. Tu, and F. Huang. The effects of audiovisual landmarks on spatial learning and recalling for image browsing interface in virtual environments. *Systems Architecture*, 117, 2021. 1, 2, 3, 8

[16] B. Gao, B. Kim, J.-I. Kim, and H. Kim. Amphitheater layout with egocentric distance-based item sizing and landmarks for browsing in virtual reality. *International Journal of HCI*, 35(10):831–845, 2019. 3

[17] B. Gao, H. Kim, B. Kim, and J. Kim. Artificial landmarks to facilitate spatial learning and recalling for curved visual wall layout in virtual reality. In *2018 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pages 475–482. IEEE, 2018. 1, 3

[18] Z. Ghaemi, K. Ananta Satriadi, U. Engelke, B. Ens, and B. Jenny. Visualization placement for outdoor augmented data tours. In *Proc. SUI*, SUI '23, New York, NY, USA, 2023. ACM. 2

[19] Z. Ghaemi, B. Ens, U. Engelke, and B. Jenny. Drawing connections: Designing situated links for immersive maps. *Proc. ACM Hum.-Comput. Interact.*, 7(MHCI), 2023. 2

[20] C. Gsaxner, A. Pepe, J. Wallner, D. Schmalstieg, and J. Egger. Markerless image-to-face registration for untethered augmented reality in head and neck surgery. In *MICCAI*, Berlin, Heidelberg, 2019. Springer-Verlag. 1

[21] D. Han and I. Cho. Evaluating 3D user interaction techniques on spatial working memory for 3D scatter plot exploration in immersive analytics. In *ISMAR*, 2023. 2

[22] S. G. Hart. NASA-Task Load Index (NASA-TLX); 20 years later. *Human Factors and Ergonomics Society Annual Meeting*, 50(9), 2006. 5

[23] S. G. Hart and L. E. Staveland. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Human Mental Workload*, volume 52 of *Advances in Psychology*. North-Holland, 1988. 5

[24] S. J. Henderson and S. K. Feiner. Augmented reality in the psychomotor phase of a procedural task. In *2011 10th IEEE International Symposium on Mixed and Augmented Reality*. IEEE, 2011. 1

[25] P. Hoghton, H. Linger, M. Cordeil, T. Dwyer, K. Marriott, and L. Visser. Where the data is: An exploratory study of mixed-reality in the wet lab domain. In *ECIS 2021*. ECIS, 2021. 1

[26] T. G. Hoog, L. M. Aufdembrink, N. J. Gaut, R.-J. Sung, K. P. Adamala, and A. E. Engelhart. Rapid deployment of smartphone-based augmented reality tools for field and online education in structural biology. *Biochemistry and Molecular Biology Education*, 48(5), 2020. 1

[27] S. Hubenschmid, J. Zagermann, D. Leicht, H. Reiterer, and T. Feuchtner. Around the smartphone: Investigating the effects of virtually-extended display size on spatial memory. In *Proc. CHI*, USA, 2023. ACM. 3

[28] J. Husár and L. Knapčíková. Possibilities of using augmented reality in warehouse management: A study. *Acta logistica*, 8(2):133–139, 2021. 1

[29] Y. Jansen, J. Schjerlund, and K. Hornbæk. Effects of locomotion and visual overview on spatial memory when interacting with wall displays. In *Proc. CHI*, New York, NY, USA, 2019. ACM. 3, 5, 7, 8

[30] K. Kost, i. Tsaramirsis, A. Patel, P. Sharma, N. Reddy, P. R, h. hawa, G. Tsaramirsis, A. Pavlopoulou, and D. Koer, Zeynep A. Ko?and Piromalis. Bio-virus spread simulation in real 3D space using augmented reality. *Engineered Science*, 16:319–330, 2021. 1

[31] E. Krokos, C. Plaisant, and A. Varshney. Virtual memory palaces: Immersion aids recall. *Virtual Real.*, 23(1):1–15, 2019. 2, 3

[32] M. Krzywinski and N. Altman. Points of significance: Error bars. *Nature Methods*, 10(10):921–922, Sept 2013. 5

[33] H. W. Kuhn. *The Hungarian Method for the Assignment Problem*, pages 29–47. Springer Berlin, Heidelberg, Berlin, Heidelberg, 2010. 5

[34] B. Lee, M. Sedlmair, and D. Schmalstieg. Design patterns for situated visualization in augmented reality. *IEEE TVCG*, 30(1), 2024. 2

[35] K. Lisanne, G. Jonathan, R. Rainer, and B. Bernhard. Investigation of eye movement measures of mental workload in healthcare: Can pupil dilations reflect fatigue or overload when it comes to health information system use? *Applied Ergonomics*, 114:104150, 2024. 5

[36] L. Lisle, X. Chen, J. Edward Gitre, C. North, and D. A. Bowman. Evaluating the benefits of the immersive space to think. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, New York, NY, USA, 2020. IEEE. 1

[37] J. Liu. AR spatial memory. `https://github.com/JiazhouLiu/AR-Spatial-Memory-Unity`, 2023. 4

[38] J. Liu, B. Ens, A. Prouzeau, J. Smiley, I. K. Nixon, S. Goodwin, and T. Dwyer. Datadancing: An exploration of the design space for visualisation view management for 3D surfaces and spaces. In *Proc. CHI*, CHI '23, New York, NY, USA, 2023. ACM. 2, 5

[39] J. Liu, A. Prouzeau, B. Ens, and T. Dwyer. Design and evaluation of interactive small multiples data visualisation in immersive spaces. In *VR*, VR '20, pages 588–597, Atlanta, Georgia, USA, 2020. IEEE. 1, 2, 5, 8

[40] J. Liu, A. Prouzeau, B. Ens, and T. Dwyer. Effects of display layout on spatial memory for immersive environments. *Proc. ACM Hum.-Comput. Interact.*, 6(ISS), 2022. 1, 2, 3, 4, 5

[41] J. Liu, K. Satriadi, B. Ens, and T. Dwyer. AR spatial memory - Effect of environmental landmarks on spatial memory. `https://osf.io/798fp/`, 2023. 3

[42] R. H. Logie, G. M. Zucco, and A. D. Baddeley. Interference with visual short-term memory. *Acta Psychologica*, 75(1):55–74, 1990. 3

[43] W. Luo, A. Lehmann, H. Widengren, and R. Dachselt. Where should we put it? layout and placement strategies of documents in aug-

mented reality for collaborative sensemaking. In *Proc. CHI*, USA, 2022. ACM. 1, 2, 3, 8

[44] W. Luo, Z. Yu, R. Rzayev, M. Satkowski, S. Gumhold, M. McGinity, and R. Dachselt. Pearl: Physical environment based augmented reality lenses for in-situ human movement analysis. In *Proc. CHI*, USA, 2023. ACM. 2

[45] T. P. McNamara and C. M. Valiquette. Remembering where things are. In *Human spatial memory*, pages 23–44. Psychology Press, 2004. 2

[46] M. A. Mehta. *Spatial Memory in Humans*, pages 1262–1266. Springer Berlin Heidelberg, 2010. 2

[47] A. Niyazov, B. Ens, K. A. Satriadi, N. Mellado, L. Barthe, T. Dwyer, and M. Serrano. User-driven constraints for layout optimisation in augmented reality. In *Proc. CHI*, CHI '23, New York, NY, USA, 2023. ACM. 2

[48] S. T. Perrault, E. Lecolinet, Y. P. Bourse, S. Zhao, and Y. Guiard. Physical loci: Leveraging spatial, object and semantic memory for command selection. In *Proc. CHI*, New York, NY, USA, 2015. ACM. 3, 7

[49] L. Piardi, V. C. Kalempa, M. Limeira, A. S. de Oliveira, and P. Leitão. Arena—augmented reality to enhanced experimentation in smart warehouses. *Sensors*, 19(19), 2019. 1

[50] V. Pooryousef, M. Cordeil, L. Besançon, C. Hurter, T. Dwyer, and R. Bassed. Working with forensic practitioners to understand the opportunities and challenges for mixed-reality digital autopsy. In *Proc. CHI*, CHI '23, New York, NY, USA, 2023. ACM. 1

[51] A. Prouzeau, Y. Wang, B. Ens, W. Willett, and T. Dwyer. Corsican twin: Authoring in situ augmented reality visualisations in virtual reality. In *Proc. AVI*, AVI '20, New York, NY, USA, 2020. ACM. 2

[52] G. Robertson, M. Czerwinski, K. Larson, D. C. Robbins, D. Thiel, and M. van Dantzich. Data mountain: Using spatial memory for document management. In *Proc. UIST*, UIST '98, page 153–162, New York, NY, USA, 1998. ACM. 3

[53] S. Ruan, J. O. Wobbrock, K. Liou, A. Ng, and J. A. Landay. Comparing speech and keyboard text entry for short messages in two languages on touchscreen phones. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, 1(4), 2018. 5

[54] K. A. Satriadi, A. Cunningham, R. T. Smith, T. Dwyer, A. Drogemuller, and B. H. Thomas. Proxsituated visualization: An extended model of situated visualization using proxies for physical referents. In *Proc. CHI*, CHI '23, New York, NY, USA, 2023. ACM. 2

[55] K. A. Satriadi, A. Cunningham, B. H. Thomas, A. Drogemuller, A. Odi, N. Patel, C. Aston, and R. T. Smith. Augmented scale models: Presenting multivariate data around physical scale models in augmented reality. In *2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, pages 54–63. IEEE, 2022. 2

[56] K. A. Satriadi, J. Smiley, B. Ens, M. Cordeil, T. Czauderna, B. Lee, Y. Yang, T. Dwyer, and B. Jenny. Tangible globes for data visualisation in augmented reality. In *Proc. CHI*, CHI '22, USA, 2022. ACM. 2

[57] M. J. Sholl and T. L. Nolin. Orientation specificity in representations of place. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 23(6):1494, 1997. 2

[58] L. Shupp, R. Ball, B. Yost, J. Booker, and C. North. Evaluation of viewport size and curvature of large, high-resolution displays. In *Proceedings of Graphics Interface*, GI '06, page 123–130, CAN, 2006. Canadian Information Processing Society. 1

[59] M.-H. Stoltz, V. Giannikas, D. McFarlane, J. Strachan, J. Um, and R. Srinivasan. Augmented reality in warehouse operations: Opportunities and barriers. *IFAC-PapersOnLine*, 50(1):12979–12984, 2017. 20th IFAC World Congress. 1

[60] D. S. Tan, J. K. Stefanucci, D. R. Proffitt, and R. Pausch. The infocockpit: Providing location and place to aid human memory. In *Proc. WPUI*, PUI '01, page 1–4, New York, NY, USA, 2001. ACM. 2

[61] B. Tversky. Distortions in memory for maps. *Cognitive Psychology*, 13(3):407–433, 1981. 2

[62] M. S. Uddin, C. Gutwin, and A. Cockburn. The effects of artificial landmarks on learning and performance in spatial-memory interfaces. In *Proc. CHI*, CHI '17, page 3843–3855, New York, NY, USA, 2017. ACM. 1, 2

[63] N. G. Vinson. Design guidelines for landmarks to support navigation in virtual environments. In *Proc. CHI*, CHI '99, USA, 1999. ACM. 2

[64] D. Waller and E. Hodgson. Transient and enduring spatial representations under disorientation and self-rotation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 32(4):867, 2006. 2

[65] X. Wang, S. K. Ong, and A. Y. Nee. A comprehensive survey of augmented reality assembly research. *Advances in Manufacturing*, 4:1–22, 2016. 1

[66] S. White, S. Feiner, and J. Kopylec. Virtual vouchers: Prototyping a mobile augmented reality user interface for botanical species identification. In *3D User Interfaces (3DUI'06)*, pages 119–126, 2006. 2

[67] W. Willett, B. Jenny, T. Isenberg, and P. Dragicevic. Lightweight relief shearing for enhanced terrain perception on interactive maps. In *Proc. CHI*, CHI '15, pages 3563–3572, New York, NY, USA, 2015. ACM. 5

[68] J. T. L. Wilson, J. H. Scott, and K. G. Power. Developmental differences in the span of visual memory for pattern. *British Journal of Developmental Psychology*, 5(3):249–255, 1987. 3

[69] F. Yang, J. Qian, J. Novotny, D. Badre, C. D. Jackson, and D. H. Laidlaw. A virtual reality memory palace variant aids knowledge retrieval from scholarly articles. *IEEE TVCG*, 27(12):4359–4373, 2021. 3, 7

[70] J. Zagermann, U. Pfeil, D. Fink, P. von Bauer, and H. Reiterer. Memory in motion: The influence of gesture- and touch-based input modalities on spatial memory. In *Proc. CHI*, CHI '17, page 1899–1910, New York, NY, USA, 2017. ACM. 8

[71] Y. Zhang, B. Ens, K. A. Satriadi, A. Prouzeau, and S. Goodwin. Timetables: Embodied exploration of immersive spatio-temporal data. In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pages 599–605, IEEE, 2022. IEEE. 2

[72] J. Zhu, S. K. Ong, and A. Y. Nee. An authorable context-aware augmented reality system to assist the maintenance technicians. *The International Journal of Advanced Manufacturing Technology*, 66:1699–1714, 2013. 1