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Evaluation of the relationship between spatial learning and image maintenance through isovist analysis

Evaluación de la relación entre el aprendizaje espacial y el mantenimiento de imágenes a través del análisis isovista

14

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ABSTRACT This study presents a method, 3D parametric isovist volumes, to examine the relationship between 'spatial visibility' and 'image maintenance.' The method assesses spatial visibility using 3D isovist analysis and investigates whether people complete a route using the 'image maintenance' method in places with limited visibility. The proposed method was applied in a three-phase case study involving ten participants from a design education background. The study employed a questionnaire, a navigation task, and a sketch-map task. Initial results indicate that spatial learning is more effective in areas with high visibility during the navigation process. However, spatial learning in low-visibility areas cannot always be predicted using the 'image maintenance' method or the data obtained from 'spatial cues.'

RESUMEN Este estudio presenta un método, los volúmenes isovistas paramétricos 3D, para examinar la relación entre la 'visibilidad espacial' y el 'mantenimiento de imágenes.' El método evalúa la visibilidad espacial a través del análisis isovista en 3D e investiga si las personas utilizan el método de 'mantenimiento de imágenes' al navegar en lugares con visibilidad limitada. El método propuesto se aplicó en un estudio de caso de tres fases que involucró a diez participantes con formación en educación de diseño. El estudio empleó un cuestionario, una tarea de navegación y una tarea de dibujo de mapas. Los resultados iniciales indican que el aprendizaje espacial es más efectivo en áreas con alta visibilidad durante el proceso de navegación. Sin embargo, el aprendizaje espacial en áreas de baja visibilidad no siempre puede predecirse utilizando el método de 'mantenimiento de imágenes' o los datos obtenidos de las 'señales espaciales.'

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PALABRAS CLAVE Isovista tridimensional, mantenimiento de imágenes, visibilidad espacial, aprendizaje espacial, navegación

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1. Introduction

This study focuses on examining route estimation in spatial learning through the image maintenance method and explores the role of visual and spatial features in facilitating this process. The aim is to propose a new method for examining the relationship between the concepts of 'spatial visibility' and 'image maintenance,' as well as the effects of spatial learning on movement within a 3D space. The study will test two hypotheses:

- Hypothesis 1: During the navigation process, spatial learning occurs more strongly in places where visibility is high.
- Hypothesis 2: Spatial learning at low-visibility points can be predicted with the 'image maintenance' method and the data obtained with 'spatial cues.'

The methodology was implemented in a 3-step case study to examine how visual capability affects cognitive domains through a 'navigation task' and spatial learning via a 'sketch map task' and 'think-aloud protocol.' The experimental phase of the navigation task took place in a small-scale 3D virtual town. By operating within a virtual environment, it becomes feasible to regulate the stimuli participants encounter and compute measurements related to the isovist. Consequently, this enables the objectification of the evaluation process.

Although the isovist is a valuable tool for assessing visual capability, it is primarily used in 2D to reduce computational complexity. However, representing the isovist on a surface fails to capture the actual dynamics of visual perception.

One of the novel aspects of this study is the method for calculating and depicting the isovist as a 3D volume. The other originality of this study lies in its endeavor to objectively assess a highly personal experience –the act of navigating an environment– by integrating various datasets obtained from the aforementioned tasks and protocols.

As previously mentioned, a blend of various theories and methods is employed to elucidate the relationship between information completion and visual capability. The subsequent subsections are dedicated to detailing these concepts of spatial learning, image maintenance, and isovist volume.

The impact of spatial visibility on spatial cognition is still an important issue in the literature, and studies in this field are ongoing (e.g., Gath-Morad et al., 2021; Fan et al., 2022; Chan et al., 2023). Given the topicality of the study subject and the proposed methodological approach, this study aims to contribute significantly to the current state of the art in the field, reflecting its impact and relevance.

1.1. Spatial learning, image maintenance, and virtual environment

When acquiring knowledge about an environment, spatial information is often accompanied by visual stimuli properties. Some studies focus on precise location of stimuli (Kelly and McNamara, 2010), while others consider the examination of visual stimulus properties (Hahm et al., 2007; Roupé et al., 2014; Dong et al., 2021).

The process of spatial cognition is closely related to spatial thinking, an important skill that enables individuals to comprehend their surroundings, engage in mental modeling, and structure problems to reach solutions (Metoyer et al., 2015); it is also the cognitive process of manipulating and analyzing spatial information (Ishikawa, 2021). Route estimations are linked to the term 'image maintenance,' a cognitive process involving the completion or prediction of spatial properties during mental imagery. Despite the absence of a full view, individuals utilize visible cues to navigate, emphasizing spatial visibility. The process of 'information completion' and the estimation of spatial information at invisible points are accomplished through the mechanism of 'image maintenance' (Kosslyn and Shin, 1991). When the desired or intended image is inconsistent during the mental imagery process, an attempt can be made to transform it by changing or restructuring its features, then, through image maintenance, the imager endeavors to align the transformed image with the intended one by adjusting its content or characteristics, ensuring continuity in the imagery process until its conclusion or cessation (Cumming and Eaves, 2018).

The extraction of metric information and spatial configuration during navigation, such as the line's direction, distances between landmarks, and turns, is closely associated with encoding in working memory (Hegarty et al., 2006). Cognitive representations of space formed during the learning process may extend beyond the initial learning standpoint, even with information from various viewpoints (Van der Kuil et al., 2021). The preservation of visual mental image equates to its recurrent recreation due to the inherent difficulty in sustaining such images over time (Kosslyn and Shin, 1991).

The acquisition of spatial knowledge can be obtained through direct experience within the physical environment (Qiu et al., 2020), and indirect experience with the help of various media and virtual environments. The most accurate way for acquiring spatial information remains direct experiences within the physical environment with virtual environments serving as the second-best alternative for learning (Richardson et al., 1999).

The acquisition of spatial knowledge from virtual environments (VE) aims to understand their space-related characteristics and serves as a substitute for actual environments. Experimental studies, including urban design simulations, analyses of legibility and wayfinding analyses, emergency response planning, and investigation into spatial usability are frequently conducted in virtual environments. These environments serve as valuable testbeds closely resembling real-world situations enabling participants to collect both spatial and visual data.

1.2. 3D volumetric isovist

The term 'isovist' was first coined by Tandy (1967), although it appears to be an extension of an older concept used by geographers to define the area visible from a specific position in the landscape, typically from a high point (Dalton et al., 2022). The concept closely tied to isovist's psychological and spatial features may have originated with Gibson's (2014) 'ambient optic array,' but it was Benedikt (Benedikt, 1979; Davis and Benedikt, 1979; Benedikt and Burnham, 1985; Benedikt and McElhinney, 2019) who drew attention to isovist's architectural importance for the first time.

An isovist is the entire volume generated by a hypothetical point with the ability to 'see' 360°. Elements within a space that obstruct visual capability and therefore affect accessibility and wayfinding ability, such as exterior walls, partition walls, and atriums, alter the boundaries of the area defined by the isovist (Benedikt, 1979).

While isovists provide accurate measurements of the geometrical attributes of an individual's point of view and viewshed, their planar representations are used for navigation behavior and wayfinding research (Wiener et al., 2007; Hölscher et al., 2012; Meilinger et al., 2009; Emo et al., 2012). However, isovists are volumetric entities, and although they are mostly reduced to 2D projections on orthographic planes (e.g., plans, sections, etc.), the actual experience of 'seeing' can be more precisely represented if the isovist is modeled conically rather than triangular.

With advancements in computational technologies, the application of 3D isovists has accelerated (Krukar et al., 2021). Various methods for calculating volumetric isovists have been introduced by Derix et al. (2008), exploring the potential effects of open and constrained spaces on navigation. Kim et al. (2019) proposed a novel metric called the 'Openness Index,' capable of capturing the structures of 3D space around an observer. Similarly, Fisher-Gewirtzman (2016) presented a 3D visibility model that considers elements of the urban environment such as roads and trees. As Lu and Lu (2019) demonstrated, 3D models, especially for multi-floor interiors, offer significant advantages over 2D isovist equivalents. 3D isovists have also been used for the analysis of orienting information during rotational locomotion (Kondyli and Bhatt, 2018) and wayfinding (Kondyli et al., 2018).

For this study, isovist volume is used as a rational instrument for measuring the spatial visibility of participants in the virtual environment, as virtual environments resemble real environment spatial learning conditions. Analyzing the size of the isovist field throughout the route, where the size of the isovist is correlated with visual capability (i.e., isovist volume is low when visibility is limited and vice versa), allows to reveal the relationship between 'image maintenance' and 'spatial visibility.'

2. Methods

This section covers the principles of the virtual environment and how the model is developed for that purpose, as well as how the 3D volumetric isovist is formed with its primary and secondary viewsheds. The setting and the steps of the case study are also explained in this section. Structure of the study is illustrated in Figure 1.

2.1. Development of the model

The subsection details the preparation phases for a 3D virtual town covering a blueprint area of 24,000 m^2. Initially, 2D simple map base layouts were created using AutoCAD software. Previous studies have shown that using 3D models instead of 2D drawings not only positively impacts wayfinding performance but also increases success rates for individuals with low spatial cognition (Verghote et al., 2019). In the second phase of model development, the 2D layout was transferred to the Rhino/Grasshopper environment for 3D modeling and 3D isovist analysis.

For individuals navigating unfamiliar destinations who need more prior information beyond their immediate surroundings, reliance on internal representations for wayfinding support is needed; moreover, they must still make navigational decisions based on the

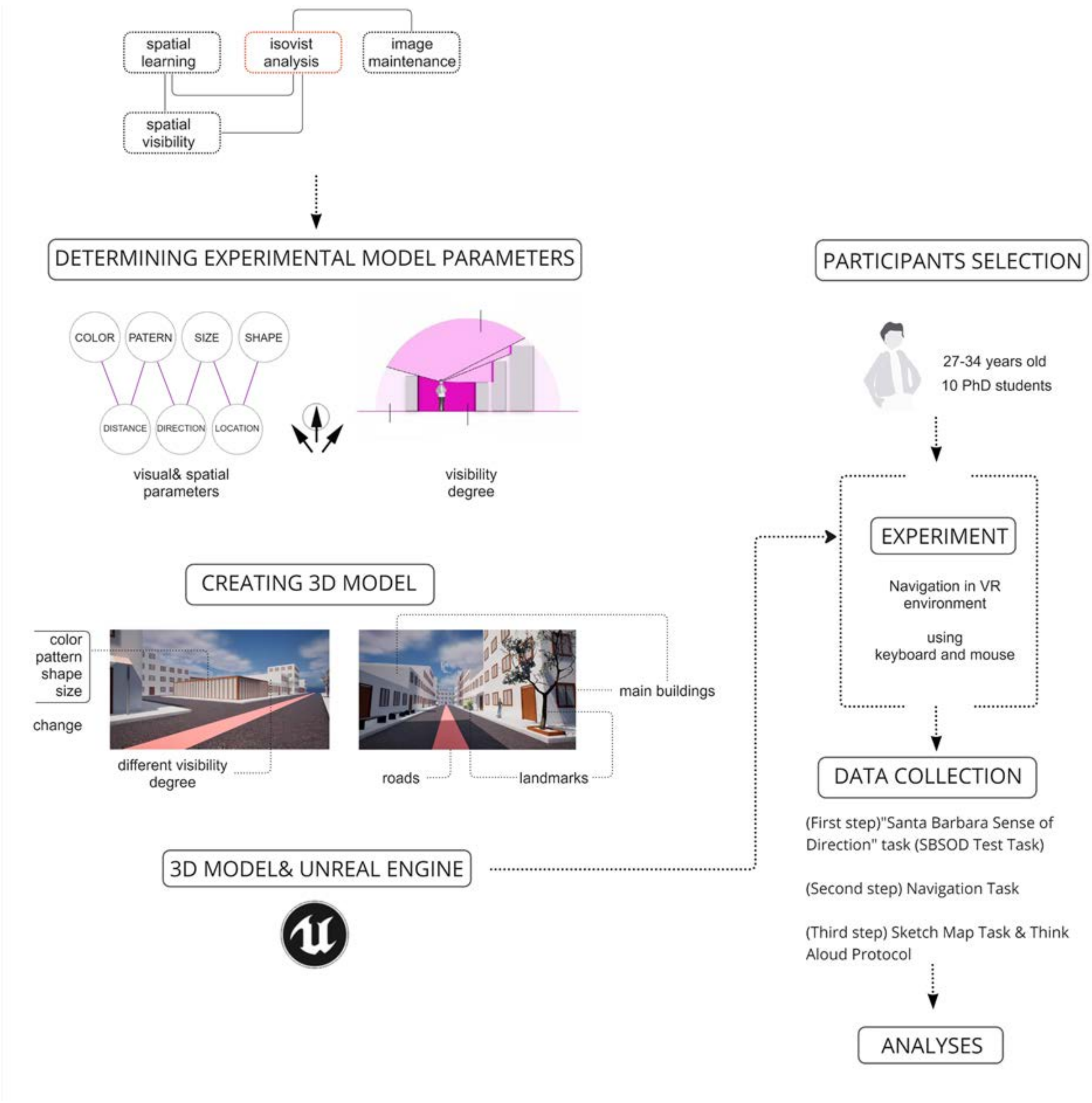

Figure 1: Structure of the study. (2024)

limited available information to reach their destination (Gath-Morad et al., 2021), Thus, a virtual environment was designed instead of using a model of an existing location to ensure that all participants had no previous experience with the place. The virtual town comprised rectangular buildings, each with a random floor height of one to five floors set at three meters each. Research conducted in the fields of environmental psychology, urban planning, and design demonstrates that the physical characteristics of the environment shape individuals' understanding of spatial features (Ahmadpoor and Smith, 2020). To provide a realistic environment within the model, some elements, such as diverse façades, trees, scaled human figures, and a dynamic sky effect, were integrated, while further detail was enhanced through variations in six building blocks and public furniture (Figure 2).

A high-resolution model was provided to participants for the experiment, which facilitated easier recollection of spatial features due to increased detail. However, certain details such as door codes were intentionally omitted to prevent participants from becoming distracted during the experiment. To maintain stimulus control, most facades, except for a few buildings, were kept white without added textures aligning with the same logic.

For the interface of the navigation task (*further detailed in Section 2.3*), the Unreal Engine was chosen allowing users to navigate smoothly in the VR environment. Camera settings and angles were configured in the model file sent to Unreal Engine ensuring a realistic first-person view aligned with that of a person with a height of 1.70 meters. A collider was integrated into the ground within the program granting users control over the first-person perspective as they moved through the model. The VR environment was displayed on an 18-inch laptop screen throughout the navigation task.

2.2. Development of the 3D volumetric isovist

The 3D isovist volumes, based on the first-person human viewpoint and the environment, were created in the Grasshopper environment. Initially, a sphere was generated to completely encompass the entire virtual town, and then subtracted from the town's ground to create a hemisphere with maximum visual capacity. A point was positioned at a height of 1.60 meters, representing the user's experimental viewpoint at the beginning of the path, illustrating the eye level of a person with a height of 1.70 meters.

To create a 3D isovist volume, 360° rays were projected from the point corresponding to eye level. Building blocks were introduced as two rows of obstacles. The first row consisted of buildings around the user's path and were in the primary field of vision while walking, while the second row represented the areas around the walking path visible with head movements. In accordance with the obstacles created, two separate 3D isovist volumes were modeled. The purple isovist volume described the user's main visual field, while the pink one described the areas the user could see while looking around (Figure 3).

Changes in the two isovist volumes could be observed simultaneously as the point defining the eye level moved (Figure 4). All volumes were overlapped to reveal the most visible areas for both the main and secondary areas generated by the 3D isovist (Figure 4).

The 3D isovist is used as an indicator of image maintenance capabilities in this research. As previously mentioned, image maintenance is a cognitive process that involves completing semi-visible areas and visual data acquired from the environment, making it directly related to the dynamic viewshed of the subject. The 3D isovist allows us to represent and, more importantly, calculate the viewsheds, which are a crucial component of the image maintenance process.

2.3. Case study

Participation in the experiment was entirely voluntary, with all participants either having normal vision or wearing appropriate medical glasses. Ten Ph.D. students took part in the experiment, comprising five females and five males, aged between 27 and 34 years old (with a mean age of 30.4). They all had a background in design education and were experts in various specific fields, including urban design, architecture, and industrial design.

Each participant was tested individually, with the experiments conducted in the same order for all participants. The experiment consisted of three main steps: the 'Santa Barbara Sense of Direction Test (SBSOD Test) task,' the 'navigation task,' and the 'sketch map task with think aloud protocol.' The tools provided on the table included a laptop and a mouse for the navigation task, as well as a tablet and a tablet pencil for the SBSOD Test task and sketch map task.

Before the experiment commenced, participants were briefed on the tasks they would be performing. They were informed that they would be drawing a map and that their voices would be recorded for analysis during the think aloud protocol. Additionally, they were told that they could explore the virtual environment freely and speak aloud for as long as they wished.

- (First step) SBSOD Test Task: The SBSOD questionnaire was employed to assess the spatial ability of the participants. Developed by Hegarty et al. (2002), this self-report scale is utilized for evaluating spatial ability. The test outcome offers a preliminary understanding of the participants' accuracy in perceiving the geometrical attributes of the environment (Burte and Hegarty, 2013).
- (Second step) Navigation Task: This step of the experiment was conducted within a virtual environment. 3D virtual environments typically feature an egocentric viewpoint, providing users with multiple perspectives on the visual information display (Hughes and Lewis, 2005). However, in this

study, only one viewpoint, namely the egocentric perspective, was utilized to prevent participants from viewing the entire layout. Participants navigated through a predetermined route, marked by a well-defined entrance and exit, highlighted with a red line, using the Unreal Engine (Figure 5a). Prior to commencing the experiment, participants were informed that they could walk and stop at any point to look around and perceive the spatial features of the overall space. No time limit was imposed for the navigation task.

- (Third step) Sketch Map Task and Think Aloud Protocol: After completing the navigation task, participants were instructed to draw a 2D map of the 3D environment they had experienced. They were asked to create a cognitive map incorporating both spatial and visual details (Figure 5b). To gain deeper insights into the participants' personal perspectives, the sketch map task was accompanied by a 'think-aloud protocol.' The think-aloud protocol involves the concurrent verbalization of thoughts during a task (Ericsson and Simon, 1993).

In alignment with Goldschmidt's (1991) methodology, the participants' verbal thoughts are recorded and subsequently transcribed into written form. The outputs of the think-aloud protocol process were analyzed based on the phrases that the participants mostly used. Since the think-aloud protocol accompanied the sketch map task, it was possible to ascertain the structure of the participants' thought process during the experiment. As participants were instructed to articulate their thoughts without any filtering during the protocol, the connection between the experiment and their thoughts is conveyed without being influenced by participant reinterpretation.

Figure 2: Various viewsheds from the virtual town along the main route. (2024)

3. Results

The result section presents the findings derived from the tasks, including the SBSOD test task, navigation task, sketch map task, and think-aloud protocol. For unbiased analysis of the findings, the identities of the participants were kept confidential while examining the result data, which were presented in tabular form whenever possible with numerical expression, and values were compared. The task results were converted into numerical data and assessed using Pearson correlation analysis to thoroughly evaluate the relationships between tasks and to reach detailed conclusions.

3.1. Results of the SBSOD test task

The outcome of the SBSOD Test is evaluated as recommended by the authors. Affirmative questions (1, 3, 4, 5, 7, 9, 14) are scored reversely, while the rest of the questions are scored correlatively. Then, the average score is calculated. The final score falls between 1 and 7, where 1 indicates a poor sense of direction and 7 indicates a good sense of direction. It's important to note that this score is only an indicator of the participant's self-assessment and expectations of their navigation abilities.

The highest score among all 10 participants was 5.7 (Participant 7) and the lowest was 2.7 (Participant 3). The average score of the sample was 4.2: two participants (3 and 8) presented a poor sense of direction, six participants (1, 4, 5, 6, 7, and 10) showed a good sense of direction, and the last two revealed an average capacity (Table 1).

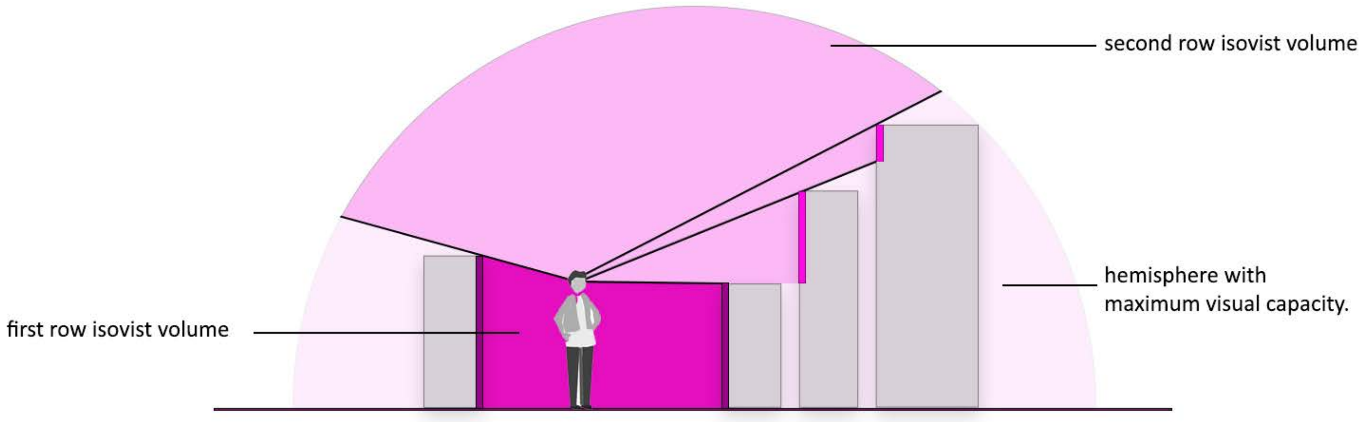

Figure 3: Development principle of the 3D isovist volume. (2024)

3.2. Results of the navigation task

The overall experience of the navigation task is assessed, focusing on the points where participants chose to stop. This analysis aims to identify significant points where participants gathered extra information by enlarging their field of view. Several parameters are considered, including 'stops and gathering information (NAV_Stops, NAV_Looking_Around, NAV_Recurrent_Path_Estimation)', 'viewshed character (NAV_Narrow Angle, NAV_Wide Angle)', and 'overall time spent (NAV_Overall_Time)'. These parameters help provide insights into participants' behavior and decision-making processes during the navigation task.

The number of stops is meaningful data for understanding the experience of the participant in gathering visual information about the surroundings. Participants sometimes stop without looking around and continue on the path; however, sometimes they deliberately stop to look around. These two actions are numerically analyzed separately. Recurrent path experiences also give characteristics to each participant's experience because some participants choose to walk the path more than once. These data are also shared in the relevant column. If the participant experiences the route more times than the number written but less than the consecutive number, it is marked with a "+". For example, if the participant walked the whole route three times but did not finish the last round, "3+" is written.

The viewshed character is assessed based on the angles participants choose to create while looking around. Voluminous, thus wider angles, suggest that participants are gathering as much information as possible at that point, as the viewpoint allows for a broader perspective. This interpretation indicates the participant's active engagement in exploring and gathering information from their surroundings.

Additionally, the overall time spent throughout the navigation task – as well as the sketch map task (*further detailed in Section 3.3*)– was an important factor in assessing the amount of information gathered during the navigation task.

The path that participants experienced during the navigation task consists of seven segments from Segment 1 (S1) to Segment 7; and eight nodes from Node 1 (N1) to Node 8; including the starting and ending points N1 and N8 (Figure 6a).

Overall, P_02 spent most of the time (09:40 minutes) on the navigation task, whereas P_033 completed the whole task in 03:30 minutes, marking the least time spent among all participants. Although P_09 spent a lot of time on the navigation task, wide viewsheds were not created, since the participant was not comfortable with the virtual interface. Therefore, P_09 was exposed to the least amount of data. Nevertheless, P_09 was mostly interested around S3, creating the widest field of view around N3. On the other hand, P_07 had the most recurrent experience of the path, stopping 35 times and looking around at 31 of them. P_07 was exposed to the most information along the path. Although P_07 created narrow angles of viewsheds more than wide angles, by moving and turning at the same time, P_07 gathered more information about the vicinity compared to other participants. (Table 2).

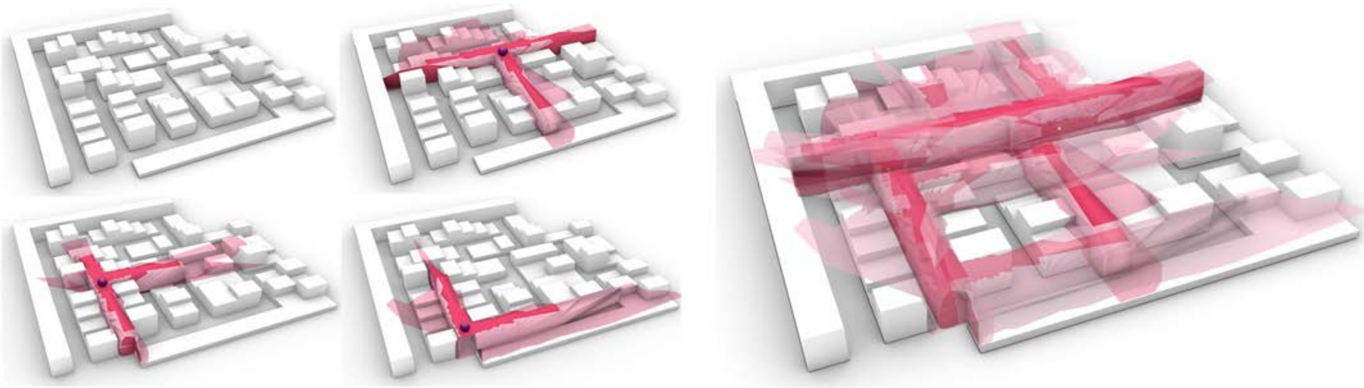

Figure 4: Main and secondary areas along with overlapped isovist volumes. (2024)

When considering the paths and viewsheds, it can be observed that participants focused more on segments between N3 and N8 compared to segments 1 and 2. In other words, wider fields of view were created throughout S3, S4, S5, S6, and S7, whereas S1 and S2 were analyzed with both fewer and narrower viewsheds. Since N3 defines a significant turning point of the whole path, participants created the widest fields of view around it (Figure 6b).

While P_01, P_02, P_06, and P_07 created wider viewsheds, P_04, P_05, and P_09 chose to experience the vicinity more with a narrower perspective. However, there were no significant differences between the narrow and wide angles created by P_03, P_08, and P_10 (Figure 6).

3.3. Results of the sketch map task

For the evaluation of the Sketch Map Task, the factors "path segment estimation (Path_Segment_Estimation)", "path segment estimation rate (Path_Segment_Rate)", "number of estimation path errors (Path_Estimation_Error)", "number of landmarks-visual expression (Landmark_Count_Visual)", "landmark visualization and properties", "number of landmarks-written expression (Landmark_Count_Written)", "written landmark properties", and "the overall sketch map drawing time (Sketch_Drawing_Time)" were considered. "Landmark visualization and properties" and "written landmark properties" were considered during the general evaluation. However, it was anticipated that these properties would not yield meaningful relationships when converted to numerical values, so they were not included in the Pearson correlation analysis.

The examination revealed the inclusion of predictable routes within the drawings, with proportions ranging from a minimum of 25% to a maximum of 90%. P_01 was identified with the highest score in route estimation (%90) also, as the second with the most visual representations of landmarks on her map (Number:14). Conversely, P_09, who generated the fewest number of route predictions, drew the map with the most landmark visualization (Number:15). However, the landmarks depicted by this participant were predominantly concentrated along the red-lined path traversed, failing to align with the route estimates. Additionally, P_03, characterized by the highest incidence of incorrect route predictions, employed a grid-based approach to map definition, resulting in route estimations extending beyond designed pathways and between adjacent structures. P_07, distinguished by the most prevalent written landmark presentation, exhibited a 30% accuracy to predictable route depiction. Despite the absence of erroneous route predictions, the participant's limited success in route estimation is attributable to an excessive focus on landmarks. As Rand et al. indicated, the information regarding the distance traveled within a space plays a supportive role in spatial learning of new environments (Rand et al., 2019). Besides, understanding

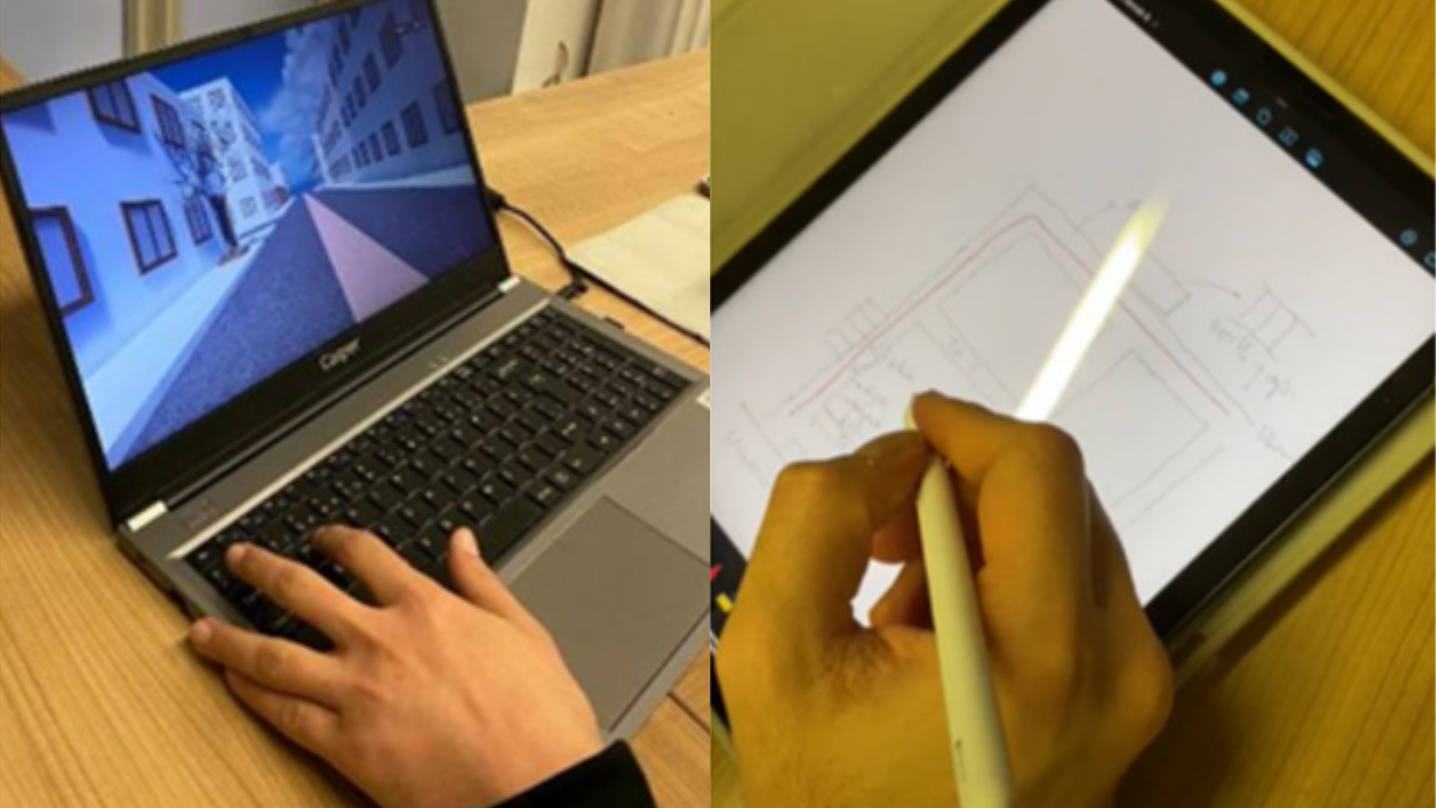

Figure 5: The setting and hardware used during the tasks. (2024)

the environment is facilitated by the sequencing and integration of a series of landmarks and their locations, thereby forming the pathways constituting the surroundings (Van Der Kuil et al., 2021). Within the scope of this study, as a general interpretation of the sketch map task result data, it was observed that the participants adopted divergent approaches in map creation, with some commencing by outlining routes while others prioritized landmark depiction, subsequently integrating routes in accordance with the depicted landmarks. Mental images can fade as soon as they are formed, so the memory representation must be continually reactivated (Kosslyn et al., 2006). During the Sketch Map Task process, some participants maintained very intense visual representations of their sketch maps. This may be because they wanted to transfer and concretize their mental images on paper before disappearing immediately. The examples of sketch- map drawings are illustrated in Figure 7; Quantitative and qualitative data in Table 3.

3.4. Results of the think aloud protocol

During the think aloud protocol, participants tended to give more environmental information at the point where they first began navigating, followed by details at intersection points along the route they walked, and lastly, they gave information about the completed area. Participants stated that they remembered the route and environmental features less during the route-drawing process. The most commonly used phrases were 'building block', 'tree', 'multi-story building', 'woman', and 'canopy' which matched the written expressions stated on the sketch map drawings. Expressions such as "the road turns right, it turns left", egocentric expressions such as "to my right, to my left" are also used when describing roads. Participants were more likely to provide details to which they were directed, expressing it as "it directed me, I walked here, the block here was very important to me, there is urban furniture here" were observed. The participants participated in the think-aloud protocol stage with the sketch map they drew, and some of them utilized their maps to aid their recall. Some participants placed question marks on the map for routes or landmarks they could not remember, then returned to update the drawing and the route progressed. Additionally, some participants expressed those differences in floor heights and variations in facades guided them. Participants also tended to adopted a systematic approach to street nomenclature, and label the streets as first street, second street, etc., and provided themselves with distance estimation data with expressions such as "as if this route was longer". In the

	Question number and answers															
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**Average**
P_01	3	6	4	6	5	6	7	3	7	6	3	5	7	6	6	5,3
P_02	4	5	2	5	2	6	1	5	2	3	6	6	3	2	5	3,8
P_03	2	3	3	3	7	5	1	2	2	1	2	1	6	1	1	2,7
P_04	7	7	6	6	3	4	6	6	6	2	4	5	4	4	5	5,0
P_05	4	3	4	3	4	5	5	5	3	5	3	6	3	4	5	4,1
P_06	6	3	6	7	4	5	6	6	6	3	6	3	2	5	6	4,9
P_07	5	5	5	6	2	6	7	7	7	6	4	7	7	5	6	5,7
P_08	3	3	2	2	4	2	3	3	3	2	5	3	3	5	3	3,1
P_09	2	5	4	3	3	1	1	3	1	6	5	7	6	3	4	3,6
P_10	6	5	2	4	1	5	7	5	5	3	4	5	6	2	3	4,2
														Overall average		4,2

Table 1: SBSOD test task results. (2024)

	Stops and sathering information			Viewshed Character		
Participant code	**NAV_Stops** (Number of stops)	**NAV_looking_ around** (Number of looking around)	**NAV_ Recurrent path experience**	**NAV_ Narrow angle**	**NAV_Wide angle**	**NAV_ Overall time (minutes)**
P_01	13	13	1+	2	11	07:00
P_02	26	23	2+	5	18	09:40
P_03	18	18	1+	9	9	03:30
P_04	27	23	2	19	4	06:10
P_05	18	12	1+	11	1	03:50
P_06	19	16	2	2	14	04:15
P_07	35	31	3+	19	12	06:20
P_08	17	14	2	6	8	04:20
P_09	11	4	1+	3	1	07:00
P_10	17	12	1+	5	7	08:20

Table 2: Quantitative data of the navigation task. (2024)

(a) Nodes and segments of the path

(b) Examples of the routes of the participants

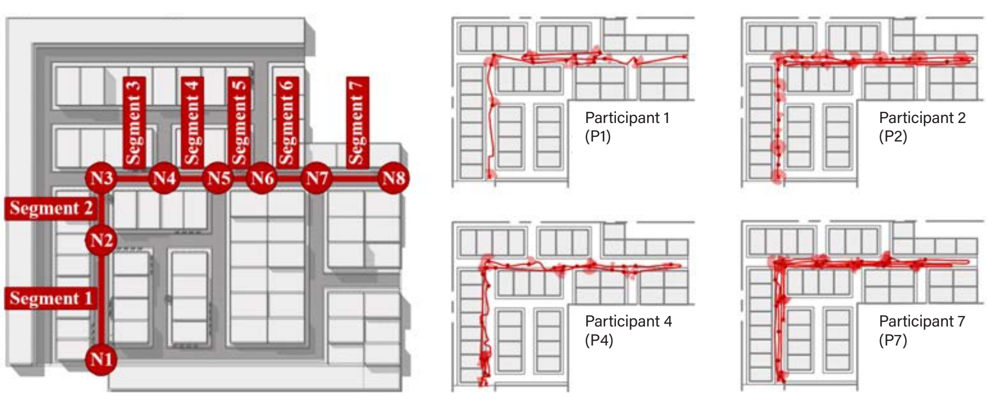

Figure 6: Outcome of the navigation task analysis. (2024)

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mental imagery process, the generation, inspection, and transformation of images take time, thus necessitating the preservation of images to facilitate the execution of these processes and the attainment of desired outcomes through the image maintenance (Cumming and Eaves, 2018). The participants were observed to use the think-aloud protocol to help preserve images during the mental imagery process and remind themselves of the environment they experienced.

3.5. Results of correlation analysis

Analyzing the correlation matrix reveals significant relationships both within and across the tasks. These insights can help understand how different cognitive and perceptual skills interrelate, providing a deeper understanding of spatial perception. To identify meaningful correlations and derive significant insight between the variables in the three tasks: "Sense of Direction Task," "Navigation Task," and "Sketch Map Task," Pearson correlation matrix (Table 4) was prepared.

Participant code	Path accuracy			Landmark accuracy				Sketch_ drawing_ time (minutes)
				Landmark_count_visual		Landmark_count_ written		
	Path segment estimation	Path segment rate %	Path estimation error		Landmark visualization and properties		Written landmark properties	
P_01	18	90%	0	14	diagrammatic expression- monochromatic **person, façade type, bench, tree	7	dark, horizon, high, 4-storey, low-rise	8:44
P_02	6.5	33%	2	6	diagrammatic expression- monochromatic **façade type, tree, bench, awning	13	color, storey numbers (1, 2, 5..), stony façade, tree, awning	11:53
P_03	12	60%	6	10	diagrammatic expression -colorful **façade type, tree, bench, awning, sections of the storey	2	furniture, single-storey	6:04
P_04	10	50%	1	10	diagrammatic expression -colorful ** buildings, bench, tree	4	storey numbers (1, 4)	6:25
P_05	7	35%	0	0	- -	5	person, sea, tree, low	1:52
P_06	9	45%	2	7	diagrammatic expression- monochromatic **building type (with hatches), section of the town	7	short, storey number (2, 3 ,4,5)	3:10
P_07	6	30%	0	6	diagrammatic expression- monochromatic **façade type, tree, herbs	15	tree, woman, cat, herbs, lane structure, multi-storey", cliff, buildings, path 1, red line, path 2, discrete building	10:55
P_08	11	55%	0	8	diagrammatic expression -colorful **bench, tree, building type (with hatches), herbs, awning	0	-	4:33
P_09	5	25%	0	15	diagrammatic expression- monochromatic **buildings, bench, tree, awning, building heights	0	-	3:22
P_10	11	55%	2	7	diagrammatic expression- monochromatic **buildings, people, cat, bench, tree, awning,	7	historical building, façade with windows, town hall, three-storey, storage, question mark, end	12:40

Table 3: Quantitative and qualitative data of the sketch map task. (2024)

Participant 1 Participant 3 Participant 9

Figure 7: Examples of sketch-map drawings. (2024)

According to the Pearson correlation matrix, significant correlations within and across tasks are explained below:

Within tasks:

Navigation task (NAV) correlations interpretation: There is a very strong positive correlation between NAV_Stops and NAV_Looking_Around (0.94), indicating that participants who stop more frequently during navigation are likely to spend more time looking around their environment. Also, another strong positive correlation exists between NAV_Stops and NAV_ Recurrent_Path_Experience (0.88), suggesting that participants who stop more frequently are more likely to experience recurrent paths during their navigation. Between NAV_Looking_Around and NAV_Recurrent_Path_Experience (0.84), there is a strong positive correlation, illustrating that as the amount of looking around during the navigation task increases, the likelihood of experiencing recurrent paths also increases. Participants who spend more time looking around are more likely to follow paths they have already traversed. The correlation between NAV_Time_Seconds and NAV_Stops (0.16) is a weak positive correlation, sugesting that there is only a slight tendency for the navigation time (in seconds) to increase as the number of stops increases.

Sketch map task correlations interpretation: Within Sketch Map results, there is an almost perfect positive correlation between Path_Segments_Estimation and Path_ Segments_Rate (0.99), showing that participants who estimate more path segments also tend to have a higher rate of path segments, indicating consistency in their sketch mapping. The correlation between Path_Segments_Estimation and Landmark_Count_ Written is approximately -0.195, indicating a weak negative correlation. It suggests that as the estimation of path segments increases, the count of written landmarks tends to decrease slightly. However, the relationship is not strong, implying that these two variables are not closely related and other factors might influence them. There is a moderate to strong positive correlation between Landmark_Count_Written and Sketch_Drawing_Time__Seconds (0.68), indicating that as the count of written landmarks increases, the time taken to complete the sketch drawing also tends to increase. This relationship implies that participants who write down more landmarks tend to spend more time on the sketch-drawing task.

Across tasks:

Sense of direction task (SOD) and navigation task (NAV) correlations interpretation: A moderate positive relationship exists between the participant's SOD_Average" and "Landmark_Count_Written, and the correlation coefficient is 0.613. This means that participants with a better sense of direction tend to write down more landmarks during the Sketch Map task. A higher Sense of Direction Task score is associated with a higher count of

ESTOA 27 / Vol 14 / 2025
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written landmarks. Participants who are better at orienting themselves and understanding spatial layouts are also more likely to identify and record a greater number of landmarks.

Navigation task (NAV) and sketch map task (sketch) correlations interpretation: The correlation coefficient 0.714 between "NAV_Looking_Around" and "Landmark_Count_Written" indicates a strong positive correlation. This means that as time spent looking around during the navigation task increases, the number of written landmarks also tends to increase. Participants who spend more time looking around during the navigation task tend to document more landmarks in written form, suggesting that looking around more frequently may be associated with a heightened awareness and recognition of landmarks, leading to a greater number of landmarks being noted down. The correlation coefficient 0.764 between "NAV_Time_Seconds" and "Sketch_Drawing_Time__Seconds" illustrates a strong positive correlation. Participants who take longer to navigate through the environment also tend to spend more time drawing their sketches. This could imply that the time invested in navigation is related to the time invested in accurately representing the environment through sketches. Longer navigation times might lead to more detailed mental maps, requiring more time to translate these maps into sketches. There is a strong positive correlation between NAV_Recurrent_Path_Experience and Landmark_Count_Written (0.741). Participants who experience recurrent paths more frequently during the navigation task tend to document more landmarks in written form. This suggests that the repetition of paths helps reinforce the memory and recognition of landmarks, leading to more landmarks being noted down. The correlation coefficient -0.429 between "NAV_Recurrent_Path_Experience" and "Path_

	SOD Average	NAV Stops	NAV Looking Around	NAV Recurrent Path_ Experience	NAV Narrow Angle	NAV Wide Angle	NAV Time Seconds	Path Segments Estimation	Path Segments Rate	Path Estimation Error	Landmark Count Visual	Landmark Count Written	Sketch Drawing Time Minutes
SOD Average	1.0												
NAV Stops	0.446	1.0											
NAV Looking Around	0.415	0.954	1.0										
NAV Recurrent Path Experience	0.447	0.888	0.842	1.0									
NAV Narrow Angle	0.323	0.778	0.698	0.539	1.0								
NAV Wide Angle	0.192	0.398	0.555	0.524	-0.208	1.0							
NAV Time Minutes	0.234	0.160	0.102	0.212	-0.158	0.324	1.0						
Path Segments Estimation	0.090	-0.382	-0.138	-0.429	-0.281	0.138	-0.100	1.0					
Path Segments Rate	0.089	-0.380	-0.136	-0.427	-0.283	0.144	-0.095	0.99997	1.0				
Path Estimation Error	-0.492	-0.019	0.134	-0.215	-0.076	0.272	-0.197	0.167	0.169	1.0			
Landmark Count Visual	-0.035	-0.421	-0.322	-0.275	-0.315	-0.073	0.214	0.388	0.388	0.029	1.0		
Landmark Count Written	0.613	0.720	0.714	0.741	0.263	0.670	0.499	-0.195	-0.191	-0.094	-0.382	1.0	
Sketch Drawing Time Minutes	0.267	0.440	0.487	0.420	0.109	0.539	0.764	0.148	0.152	0.117	0.024	0.682	1.0

Table 4: Pearson correlation analysis. (2024)

Segments_Estimation" indicates a moderate negative correlation. This means that as the experience of following recurrent paths during navigation increases, the estimation of path segments tends to decrease. Participants who experience recurrent paths more frequently during the navigation task tend to estimate fewer path segments. This could imply that familiarity with the environment gained through recurrent paths simplifies their mental representation of the path structure. Both accuracy and speed of perception in wayfinding and spatial orientation tasks are enhanced by increased familiarity with the environment (Kim et al.,2021). The repeated traversal of the same paths may reduce the perceived complexity of the environment, resulting in lower estimates of path segments.

4. Discussion and conclusions

All datasets gathered from aforementioned analysis are combined to achieve a comprehensive understanding of the impact of spatial visual perception. In accordance with Hypothesis 1, during the navigation process, spatial learning occurs more strongly in places where visibility is high. It can be asserted that the accuracy of this hypothesis was validated as participants demonstrated improved estimation accuracy along the main walking axis and its immediate intersection, where 3D isovist volumes are densely distributed.

In line with the comparison of the experimental outputs and 3D isovist volumes, it is inconclusive to definitively assert the validation of Hypothesis 2, since not all participants estimated the predictable areas using intrinsic image maintenance tactics. However, the observation that one participant achieved a prediction rate of 90% suggests further exploration of this hypothesis. Additionally, half of the participants achieved at least 50% success in route prediction, indicating potential validity of Hypothesis 2 in certain scenarios. Making inferences from missing information is a very important cognitive process that allows the recognition of partially visible or hidden objects through pattern completion during visual perception (Tang, 2017) and image maintenance. One possible reason the second hypothesis could not be fully confirmed could be the cognitive differences among participants.

Further investigation into these scenarios accounting for individual differences and environmental factors is warranted. Although building heights were utilized as data for route estimation, analysis of both the sketch map task and think-aloud protocol data revealed that changes in building facades also provided significant visual cues. Participants predominantly focused on the quantity and quality of landmarks, whereas their precise locations, distances from each other, and their positions along the route remain absent from the outputs. The study is subject to some limitations, including participant sample size and education background as well as the variations in experimental environments. All ten participants in the study have a design education background. The study outcomes may differ in the scenario with a large number of samples from different disciplines. Differences in age range, gender, and occupational groups demonstrate variations in cognitive skills, especially in the navigation process (Nazareth et al., 2019). Working with different target groups may yield varying outcomes. For this research, we started with designers. Future research may include different yet homogeneous target groups profession-wise, allowing for reasonable comparisons over time.

Integration of 3D isovist volumes into the navigation task interface would enable simultaneous observation of participants' isovist volumes during the navigation task. As further studies, the research could encompass varying spatial and visual elements within environmental settings, differentiating the participant demographic structures, and providing a setup in which individual differences can be analyzed by converting them into quantitative data.

The results of this experiment, which investigates the effect of environmental visibility on spatial learning, will contribute to both the literature and real-life applications. Our findings indicate numerous potential real-life applications with rapidly advancing technology and the increasing use of digital tools. For example, navigation devices can be optimized by incorporating visibility data to provide more effective routes. While there is potential for utilizing our findings, the clarity and comprehensibility of our experimental setup and methods allow for the development of new experimental sets and their use in research fields. Including the effects of spatial learning and visibility in the design of optimized and personalized navigation tools can serve the most optimal use for individuals with cognitive differences. Our insights into the contribution of this study to urban planning are aimed at helping design cities that are easier to navigate, enhancing both pedestrian and vehicular movement. Additionally, economic benefits may arise from improved wayfinding in commercial areas, leading to increased foot traffic and sales. The potential applications extend beyond these examples, opening avenues for further innovation. Our study will contribute significantly to the literature and offer practical applications, especially in light of rapidly advancing technologies.

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