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The Impact of prior survey knowledge and Virtual global landmarks on spatial knowledge acquisition

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STATEMENT OF INTEGRITY

I Hala Abdelmaksoud Hamed Ghareeb, declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

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Tasks	NO	YES	Generative Artificial Intelligence tools
Better understand issues related to the research		✓	ChatGPT (for support& I didn't depend on its interpretation)
Summarizing text from bibliography / resources		✓	ChatGPT, Scispace
Summarizing the method(s) used		✓	ChatGPT, Scispace
Find relative papers		✓	Litmaps
Translating text	✓		
Grammar check	✓		
Paraphrase or rewriting text from other people / resources		✓	ChatGPT (it helps with brainstorming)
Coding in MS excel		✓	ChatGPT (codes were verified the codes)
Get help on a software		✓	It helps to
Creating and editing images, maps, videos, etc.		✓	Google Gemini
Enhancing my own English text not generating content		✓	Paperpal
Recommending structures of the chapters		✓	ChatGPT

DEDICATION

This thesis is dedicated to the soul of the man who always believed in me, who taught me to follow my passion, and to the one I strive every day to make him proud. I wish you were here to see me at this stage of my life. To my father—until we meet again.

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The Impact of prior survey knowledge and Virtual global landmarks on spatial knowledge acquisition

ABSTRACT

During daily navigation, such as commuting to work or returning home, individuals observe their surroundings and acquire spatial knowledge of routes and environments passively which influence their comprehension of routes and environments. Within the taxonomy of wayfinding, it remains uncertain whether the path-following tasks differ cognitively when navigators possess survey knowledge of the broader areas. Additionally, the application of video-based wayfinding with Virtual Global Landmarks (VGLs) remains unexplored. This study examines the different types of spatial knowledge acquired by young adults through a simulated route-following task on an unfamiliar route, under varying conditions of survey knowledge availability. Spatial knowledge acquisition was assessed through eight tasks with Bayesian analysis to test the gained landmark, route, and survey knowledge. The findings indicate that prior survey knowledge of the broader environment did not impact the acquisition of landmark or route knowledge along a new route of navigation. However, the results suggest that understanding of directional relationships between landmarks on a novel path of navigation was enhanced when survey knowledge of the surrounding areas was available. These results contribute to wayfinding research by clarifying the role of survey knowledge of the broader spatial context in shaping spatial learning along unfamiliar routes and by demonstrating the effectiveness of VGLs in novel methodological approach using videos.

KEYWORDS

Spatial Knowledge; Taxonomy of wayfinding; Virtual global landmarks; Navigational Video; Path-following

Sustainable Development Goals (SGD):

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ACRONYMS

AR – Augmented Reality

H_0 – The null hypothesis of the statistical test

H_1 – The alternative hypothesis of the statistical test

IFGI – Institute for Geoinformatics at University of Münster

NOVA IMS – Information Management School at NOVA University Lisbon

VEs – Virtual Environments

VGLs – Virtual global landmarks

VR – Virtual Reality

1. INTRODUCTION

Human wayfinding is an essential process that enables individuals to move and make decisions to efficiently reach their destination within their environment (Farr et al., 2012). Spatial learning is fundamental for effective human navigation as it enables individuals to facilitate decisions during wayfinding and enhance environmental comprehension (Burte & Montello, 2017; Wen et al., 2011; Wiener et al., 2009).

Wiener et al.(2009) introduced a taxonomy to differentiate wayfinding tasks, wherein the type of spatial knowledge serves as a central criterion for classification. Consequently, understanding the types of spatial knowledge involved in a wayfinding task is crucial for research studies in wayfinding and spatial cognition. Research distinguished three types of spatial knowledge: Landmark knowledge is the knowledge about an notable feature or a landmark in space, route knowledge refers to a sequential representation of landmarks and their associated actions within a route, and survey knowledge involves a map-like configurational understanding of the spatial layout of an environment (He et al., 2019; Muffato et al., 2023).

Repeated exposure to an environment significantly influences the acquisition of survey knowledge, which is the most complex form of spatial knowledge development. Prior survey knowledge plays a crucial role in facilitating spatial learning during wayfinding. It contributes to the development of cognitive maps, improves self-orientation and self-localization while navigating a route, and facilitates understanding of the spatial relationships between landmarks in terms of distance and direction(Alinaghi & Giannopoulos, 2024; Chen & Li, 2020; Chrastil & Warren, 2015; Demirbaş, 2001; He et al., 2019; Wen et al., 2011).

In wayfinding research, two types of landmarks are identified: local landmarks, which are situated close to the route, and global landmarks, which are more distant (Galvão et al., 2021; Winter et al., 2008). Recent studies have introduced the concept of virtual global landmarks, which are not visible to the human eye but can be perceived through a system that displays distant scenes to aid navigators in becoming more aware of their surrounding areas (Liu, Singh, Wunderlich, et al., 2022; Singh et al., 2021).

1.1 RESEARCH GAP AND PROBLEM STATEMENT

While earlier studies like (Chen & Li, 2020; Chrastil & Warren, 2015; He et al., 2019; Wen et al., 2011) primarily examined how survey knowledge of the immediate navigation area influences navigation performance and spatial learning, the role of possessing survey knowledge about surrounding spatial context received little attention.

The taxonomy of human wayfinding is well-structured and offers a robust framework for classification. However, the authors of (Wiener et al., 2009) describe their work as a foundational taxonomy, allowing for further refinements. Frank,(2009) suggested that the resulting tasks requires classifications. Particularly concerning the path-following task, Schwering et al.,(2017) argue that this task should be classified when survey knowledge about the broader environment is considered.

1.2 RESEARCH AIM AND OBJECTIVES

In light of the limited research concerning the impact of prior survey knowledge about the broader environment on path-following wayfinding tasks involving unfamiliar routes, this thesis aims to investigate and evaluate influence of such pre-existing knowledge on acquiring the diverse types of spatial knowledge through using a navigational video from first-person perspective with embedded virtual global landmarks (VGLs), the following section (1.3 Methodological Approach Overview) describes and justifies this methodological approach.

The study pursues two primary objectives. First, it aims to identify the cognitive tasks associated with each type of knowledge that are influenced by having prior survey knowledge of the broader environmental configuration using the proposed approach of the study. Second, it seeks to evaluate the effectiveness of the proposed methodology through demonstrating its practical contributions and how it facilitates the spatial learning process.

1.3 METHODOLOGICAL APPROACH OVERVIEW

This thesis presents an experimental study that compares the spatial knowledge acquired under different survey knowledge conditions among two groups of adults engaged in a simulated path-following wayfinding task. This task involves navigating through a first-person video with embedded virtual global landmarks (VGLs) displayed virtually via 2D silhouetted views along the route.

This approach is justified for the following reasons: Firstly, to conduct this study, navigators will be categorized into two groups based on their prior knowledge of the surrounding spatial context of the study area, thereby allowing for evaluation of the impact of this knowledge. Secondly, all participants should be able to view distant landmarks, such as towers, statues, or wide features like mountains or rivers, to become more aware of their surroundings. This methodology proposes a novel approach utilizing navigational first-person video which can be viewed through conducting an online experiment, allowing us to recruit participants who do not have any prior spatial knowledge about the environment around the study area. The video incorporates virtual global landmarks, enabling us to equally present the surroundings of the navigation route to all participants.

This approach has the potential to address the current limitations of not being able to view surrounding areas from navigational routes by offering access to view external areas without requiring costly equipment or complex systems.

1.4 RESEARCH QUESTIONS AND HYPOTHESES

To address the research problem and respond to the identified gaps in literature, the following research question is proposed:

RQ: *What is the influence of prior survey knowledge about the broader environment on the acquired knowledge in a simulated path-following wayfinding task with embedded VGLs through a first-person video?*

The study proposes hypotheses concerning the different types of landmarks:

H1: Navigators with survey knowledge about the broader environment will show better performance in recalling landmarks, the sequence of landmarks and routes taken along a route.

H2: Navigators with survey knowledge about the broader environment will be able to provide more correct answers in survey knowledge tasks.

> **-H2a:** Navigators with survey knowledge about surrounding environment will build more precise mental representation of the route

-H2b: Navigators with survey knowledge about surrounding environment will be aware of the camera location and orientation along the path

-H2c: Navigators with survey knowledge about surrounding environment will be able to provide more precise relative directions and distance estimation

1.5 THESIS STRUCTURE

The subsequent sections of this thesis are organized as follows:
Chapter 2 – literature review: This chapter provides a literature review on the key concepts in wayfinding research, and the gaps in the current studies with a focus on spatial knowledge, learning, and survey knowledge impact. It also highlights methodological approaches.

Chapter 3 – Methodology: This chapter presents the research design, participants, and study area, followed by a description of the materials, procedures, and measures used in the study. It also outlines the data preparation and statistical analysis approach, and ethical considerations.

Chapter 4 – Results: This chapter reveals the results for all the tasks related to each type of knowledge by demonstrating the descriptive and statistical analysis.

Chapter 5 – Discussion: This chapter provides interpretation of the results obtained from each task, aiming to confirm the hypotheses and answer the research question. Then it addresses the limitations, implications, and future directions.

Chapter 6 – Conclusion: This chapter presents the final conclusions of the study.

2. LITERATURE REVIEW

2.1 INTRODUCTION TO WAYFINDING

Wayfinding is a daily task that involves moving from one location to a destination. Moreover, it is a complex cognitive process at which the individuals can identify their spatial orientation and it combines a person's perception with environmental settings, allowing navigators to form mental representations that guide them to make decisions along the way, and it can occur in either indoor or outdoor contexts within familiar or unfamiliar environments (Farr et al., 2012; Golledge, 1999; Montello, 2005; Schwering et al., 2017; Wiener et al., 2009).

Wayfinding activities include various tasks like exploring spaces, searching for a place, and following a route. Wiener et al. (2009) indicated that navigating to new places is one of the most important applications of spatial cognition and it includes various tasks like exploring spaces, searching for a place, and following a route, each task includes different cognitive processes, therefore in a more detailed classification was introduced for better understanding of each task and be able to differentiate and compare the different tasks.

THE CURRENT TAXONOMY OF WAYFINDING TASKS

Wiener et al. (2009) structured an initial taxonomy, Figure 2-1, of the different wayfinding tasks based on the spatial knowledge level approach to unify a classification for other researchers to use it for the following research.

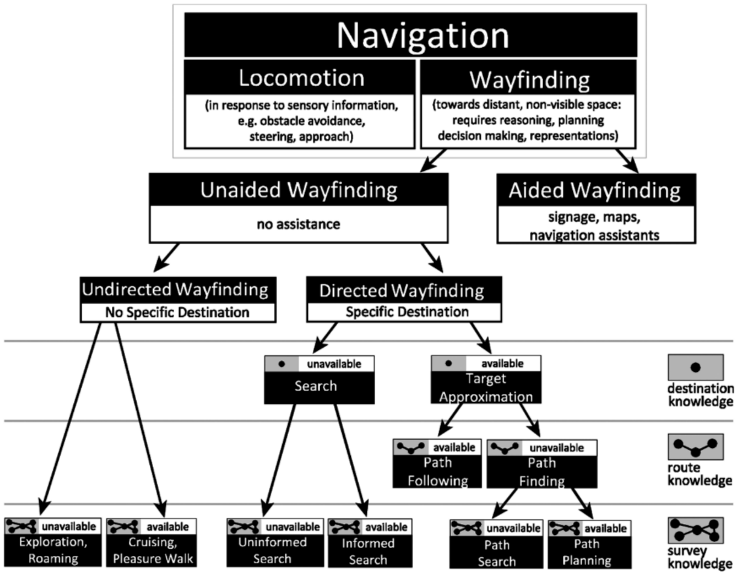

Figure 2-1 The proposed taxonomy of wayfinding tasks by Wiener et al. (2009)

The taxonomy diagram, Figure 2-1 , illustrates how human navigation is divided into two main components; locomotion, when navigators use sensory inputs from the surroundings to move on the way in their visible environment like steering and avoid obstacles and does not need spatial memory to perform it (Mallot, 1999; Montello, 2001, 2005) as cited by Wiener et al. (2009), while the other component is wayfinding which includes more cognitive processes and requires decision making.

The taxonomy shows how wayfinding is categorized according to the existence of assistance, whether the targets are identified and the spatial knowledge available to the navigator.

Human wayfinding tasks are first classified into aided and unaided categories; aided tasks are supported by the help of signs on the way that guide the rivers, or maps that can be found in streets to direct us to our destination, the unaided tasks that humans implement without any assistance.

Wiener et al. (2009) classify unaided wayfinding tasks into directed and undirected categories, and their subcategories are identified by the availability of the different kinds of spatial knowledge. Undirected wayfinding is a navigation process without a specific goal, and it is divided by survey knowledge into casual walking in familiar areas, and exploration of novel environments.

In contrast, directed wayfinding has five different tasks; directed wayfinding has two categories based on the knowledge of targeted destination: search and target approximation. Search classification involves two tasks: Uninformed search, which occurs when the navigator possesses a goal but lacks knowledge of the environment, thereby relying on trial and error; and Informed search, which involves familiarity with the environment but not the precise location of the target.

Path following utilizes route knowledge to reach a known destination, such as commuting to work. In contrast path finding occurs when route knowledge is absent and it is subcategorized into: Path search which happens when the destination is known but the route is not, requiring visual cues to find the way, and path planning involves knowing both the destination and the environment’s layout, allowing the navigator to mentally plan an efficient route.

2.2 THE ARGUMENTS AND GAPS IN THE CURRENT TAXONOMY

Wiener et al. (2009) developed a well-structured taxonomy, while also acknowledging it as a primary framework, thereby leaving room for further development by other researchers. Other scholars have explored the limitations and gaps in the taxonomy of human wayfinding tasks. For instance, Frank (2009) mentioned that the current taxonomy does not define all the taxa. Especially the unaided wayfinding category that Frank suggests that it obtains more tasks.

While the taxonomy mentioned in (Wiener et al., 2009) does not specify any relation between path-following tasks and survey knowledge, Schwering et al. (2017) argues that there is a subcategory that should be added to path-following tasks regarding the existence of survey knowledge that allows navigators to update their path dynamically based on broader spatial understanding of an environment.

Schwering et al. (2017) and Frank (2009) recognized that, although Wiener et al.’s taxonomy offers a valuable foundation, it necessitates refinement to encompass all types of spatial knowledge involved in real-world navigation.

2.3 SPATIAL KNOWLEDGE

The term spatial knowledge refers to the information including locations of places and landmarks, distances between them, and their directional relations. Understanding of these spatial information supports a successful wayfinding (Chen & Li, 2020). Through navigation, we gain the spatial knowledge about the environment through a first-person view (Muffato et al., 2023). Additionally, Qiu et al. (2020) clarified that gaining spatial knowledge is fundamental to solve the spatial problems and depends on constructing a comprehensive representation of the environment. According previous studies like (Chen & Li, 2020; Kim & Bock, 2021; Löwen et al., 2019; Siegel & White, 1975), spatial knowledge can be categorized into three types:

Landmark knowledge refers to the knowledge about a point or a scene in space that people use to recognize a route. The identification of landmarks is a key factor in building a mental representation about the environment which supports individuals in orientation and location identification along a route (Afrooz Aida E. et al., 2014; He et al., 2019; Muffato et al., 2023; Omer & Goldblatt, 2007).

Route knowledge is the knowledge about sequences of points or paths formed while traveling a route (Afrooz Aida E. et al., 2014; Muffato et al., 2023; Münzer et al., 2006; Omer & Goldblatt, 2007; Wen et al., 2011). Meanwhile, He et al.(2019), Chrastil & Warren(2015), and Chen & Li.(2020) described it as a series of landmark-action associations and decisions at points in the route which enable navigators to reach the following point in a route.

Survey knowledge is configurational understanding and a map-like mental representation of the spatial relationships between multiple points in an area including distances, directions, scales and layouts (Bertel et al., 2017; Chrastil & Warren, 2015; Meilinger et al., 2013; Omer & Goldblatt, 2007; Wen et al., 2011). Muffato et al.(2023) and Münzer et al.(2006) indicated that survey knowledge is understanding the spatial relationships between at landmarks unlike the route knowledge which focus only on the order of points in the route.

2.4 TYPES OF LANDMARKS

Landmarks are recognizable features or scenes in an environment; they are used as reference points for orientation (Egenhofer & Mark, 2002; Galvão et al., 2021; Jamshidi & Pati, 2024; Manganelli, 2016).

In classical approaches, landmarks have been categorized based on their function and proximity to routes into two types: local and global landmarks(Galvão et al., 2021; Steck & Mallot, 2000; Winter et al., 2008). However, landmarks can be categorized by shape into point-like and polygonal forms(Galvão et al., 2021).

Local landmarks are objects, like buildings, parks, or playgrounds, situated along a route or nearby, and easily memorable due to their distinctive characteristics. These landmarks serve a crucial function as decision and reference points, ensuring that a navigator remains on the correct path(Galvão et al., 2021; Schwering et al., 2017; Steck & Mallot, 2000).

Global landmarks, also known as distant landmarks, are features such as towers or mountains that are situated far from navigational routes but remain visible(Galvão et al., 2021; Schwering et al., 2017; Winter et al., 2008). These landmarks support navigators with maintaining their bearing towards a distant target by providing compass information(Steck & Mallot, 2000).

2.5 VIRTUAL GLOBAL LANDMARKS

Recent studies have introduced a new concept: *Virtual global landmarks (VGLs)* are characterized as distant real-world elements that are displayed virtually using an augmented reality system. This system enables individuals to see these landmarks even when they are obscured from view along a navigational route due to physical barriers, thereby enhancing awareness of the surrounding environment. Singh et al.(2021) and Liu, Singh, Wunderlich, et al.(2022) employed VGLs as reference points, irrespective of the navigator's position, to facilitate spatial learning through map-based methods and to assist navigators in determining their orientation and relative positions to the VGLs.

System introduced by Liu, Singh, Wunderlich, et al.(2022) is designed to maintain continuous spatial referencing during navigation by being always displayed as long as they are in the users' sight and they were demonstrated in heads-up display. VGLs were viewed in 2D silhouettes of the real landmarks of the study and shown within an AR environment, hence even when the navigators turn or move within the environment, the landmarks are always maintained viewed in their real direction whenever the navigators look at them.

The literature indicates that using VGLs supports spatial learning and enhances location awareness within the surrounding and outer environment. In the context of navigation, VGLs improve angular accuracy. This system allows individuals to maintain awareness of their orientation, thereby assisting them in selecting shorter routes to their destinations(Liu, Singh, & Lin, 2022; Liu, Singh, Wunderlich, et al., 2022; Singh et al., 2021).

2.6 SPATIAL KNOWLEDGE ACQUISITION DURING WAYFINDING

Spatial knowledge acquisition is the processes of developing a mental map of an environment by learning distance and directions judgement between landmarks and the order of places in a route during wayfinding(Burte & Montello, 2017; Chen & Li, 2020).

To understand how to gain spatial knowledge, the following subsections review the learning stages and how to gain each type of knowledge, modes of learning, and the different environments and each one affects the learning process.

2.6.1 LEARNING STAGES

According to Siegel and White (1975), the acquisition process of spatial knowledge occurs sequentially, beginning with landmark knowledge, followed by route knowledge, and finalizing in survey knowledge. However, Ishikawa and Montello (2006) as cited by He et al.(2019), demonstrated that the different kinds of spatial knowledge can be acquired at the same time after the initial exposure to an unfamiliar environment.

subsequent studies supported that the method of learning influences the order in which these types of spatial knowledge are developed, for instance, the environments of the studies weather real or virtual affect the learning process about an environment (Münzer et al., 2006; Qiu et al., 2020). Furthermore, other research suggests that survey knowledge is constructed alongside route knowledge (Bertel et al., 2017), while other researchers clarified that survey knowledge is developed through advanced cognitive processing of both landmark and route knowledge (Ahmadpoor & Shahab, 2019; Qiu et al., 2024), Qiu et al.(2024) identified survey knowledge as the most challenging type to acquire from a single visit.

2.6.2 NAVIGATION MODE OF LEARNING

The mode of navigation is intended to be based on an individual's interaction with their environment during the navigation process (Afrooz et al., 2018; Qiu et al., 2020).

Active mode, happen when the navigator learning spatial knowledge through interactions with the environment, he/she might be a pedestrian, biker, or driver in real world settings, and they can troll their movement in a virtual environment (Afrooz et al., 2018; Muffato et al., 2023; Qiu et al., 2020).

Passive mode, happens when individuals are not involved in the wayfinding process but observe the route, the learning process only needs their attention, like passengers in a bus or in a taxi, in real area, or through the exposure of a video, limited cognitive control (Afrooz et al., 2018; Qiu et al., 2020).

Afrooz et al.(2018) suggests that active navigators develop superior survey knowledge and mental maps compared to passive travelers. Conversely, Qiu et al. (2020) found from their results that passive learning can be as effective as active learning with the aid of virtual street view maps, and even more efficient, it may facilitate spatial knowledge acquisition more efficiently than active learning. The same study conducted by Qiu et al. (2020) revealed that passive learning, facilitated through video observation in real-world contexts, showed more accurate results in a scene recognition task compared to active learning methods, this finding suggests that passive learning optimizes attention and minimizes distractions. This finding contrasts with the study by Afrooz et al. .(2018), which indicated that scene recognition results from active learning were statistically more accurate than those from the passive learning group in a built environment.

2.6.3 ENVIRONMENTS IN WAYFINDING RESEARCH

In the reviewed studies, many researchers used one or more of these environments, or a mix of them.

Real world environments, the physical environment is the most utilized setting in wayfinding research due to its superior results, especially in spatial knowledge representation because of the physical interaction during the knowledge acquisition as it provides non-visual but sensory channels, such as smelling, hearing, and touching (Afrooz et al., 2018; Qiu et al., 2020).

Virtual environments (VEs), are generated using 3-D modelling software and crafted for navigation experiments and can be used with both active and passive learning, this kind of environments is used in several wayfinding research studies like (Chrastil & Warren, 2015; Steck & Mallot, 2000; Waller et al., 2004), and also known as virtual reality (VR).

Environments with Augmented Reality (AR), this system refers to a technology that use digital information onto the physical world or onto VEs, thereby enriching navigators experience with extra information that provide navigational aids for example VGLs were used to provide extra aid for orientation (Liu, Singh, Wunderlich, et al., 2022; Singh et al., 2021).

Video recording, this method requires participants to be exposed to a navigation video of a route, These videos are utilized not only in real-world route settings but also in (VR) environments for example Muffato et al (2023) used a navigation video of VE in a path learning task, and Chrastil & Warren(2015) employed a video of one of their Experimental conditions, documenting movement within a VR-constructed maze for exploration purposes.

2.7 IMPACT OF SURVEY KNOWLEDGE ON WAYFINDING TASKS

Survey knowledge typically refers to an map-like representation of an environment, enabling the understanding of global spatial relationships, such as distances, directions, and layouts, among multiple locations, rather than a sequence of actions (Chrastil & Warren, 2015; Steck & Mallot, 2000; Zhong & Kozhevnikov, 2016).

By understanding the configurations of an environment, survey knowledge facilitates understanding the relationships between locations and route in tasks such as estimating distances and directions, providing relative directions between landmarks, retracing routes, and creating sketch maps (Chen & Li, 2020; Chrastil & Warren, 2015; He et al., 2019; Wen et al., 2011). Furthermore, survey knowledge facilitates comprehension of the layout of an environment, as noted by Demirbaş(2001), citing(Rossano et al., 1999).

Becoming familiar with an environment significantly impacts the acquisition of survey knowledge. As one becomes more accustomed to the environment, a more adaptable spatial understanding is formed(Demirbaş, 2001; Li & Klippel, 2016). Moreover, the study (Alinaghi & Giannopoulos, 2024) revealed that the prior knowledge about an environment enables navigators too implement a self-localization task faster.

Acquiring configurational knowledge of a space about objects or landmarks provides long term understanding of that environment (Zhong & Kozhevnikov, 2016). Hence, even after leaving a city individuals still understand the settings of that city.

2.8 VIDEO-BASED WAYFINDING

In earlier research, video-based wayfinding is an approach of passive spatial learning that involves learning a route by watching a recorded video of first-person or someone else navigating the route. It is usually used to assess the gained spatial knowledge (Hegarty et al., 2006; Muffato et al., 2023; Qiu et al., 2020; Wen et al., 2011), other studies unutilized videos in active learning techniques for example (Chang & Wang, 2010) used videos to give assistance during navigation within indoor settings, while Chrastil & Warren (2015) used short videos for route between objects in a virtual maze in passive and active learning tasks.

Previous studies used video-based testing for the assessment of multiple tasks related to all types of spatial knowledge like scene recognition(landmark identification) by showing pictures of landmarks that appear in a testing video, route choice to assess the learned route by showing pictures of decision points then asking about the action done there, direction and distance estimation tasks, orientation identification while facing a landmark on the route, and Map-Sketching to analyze individuals understanding of an environment (Hegarty et al., 2006; Qiu et al., 2020; Wen et al., 2011).

Spatial learning through video has received limited attention so far; however, evidence from previous studies suggests promising potential for future implementations. Participants could maintain orientation during navigation in VEs with active navigation experience or passive learning through videos (Qiu et al., 2020) as cited from (Allison & Redhead, 2017), Hegarty et al.(2006) mentioned that learning from a video or VR can be adequate as the real world environment. Video based system showed higher efficiency than other media like photographs in a prompting system of aids in active navigation (Chang & Wang, 2010).

The reasons to use a navigational video paradigm in wayfinding to assess spatial knowledge: Videos simulate passive spatial learning similar to real-world experiences of passengers or first-time visitors (Muffato et al., 2023). Moreover, video-based methods are cost-effective, scalable, and safe for vulnerable populations, making them a practical alternative to real-world or virtual reality navigation tasks (Qiu et al., 2020).

2.9 BAYESIAN ANALYSIS INFERENCE

Bayesian analysis is a statistical methodology used to update prior beliefs or knowledge about hypotheses based on observed data by generating posterior probabilities. This approach addresses evidence by evaluating hypotheses through assessing the relative likelihood of an entire distribution of hypothesized values for an effect. Unlike classical analysis, which involves accepting or rejecting a null hypothesis, Bayesian analysis quantifies the evidence (Berkhout et al., 2023; Faulkenberry et al., 2020; Van Doorn et al., 2021; Young, 2019).

This statistical approach produces Bayes factors, which are important components of Bayesian inference. These factors serve as a statistical measure to quantify the evidence for one hypothesis over another, providing a ratio that expresses the degree to which the observed data favor one hypothesis compared to the other (Goss-Sampson, 2020; Van Doorn et al., 2021).

The first Bayes factor (BF_{10}): is the ratio between the probability of the data under the alternative hypothesis (H_1) to the probability of the data under the null hypothesis (H_0) and can be represented by Equation 1, hence when BF_{10}>1, it indicates that the probability of the data under the alternative hypothesis (H_1) is higher than the probability of the data under the null hypothesis (H_0) and providing evidence for H_1 (Faulkenberry et al., 2020; Goss-Sampson, 2020).

$$BF_{10} = \frac{p(data \mid H_1)}{p(data \mid H_0)} \quad \textbf{Equation 1}$$

Where $p(data \mid H_1)$ and $p(data \mid H_0)$ represent the probability of the data under the alternative and null hypothesis $H_1$and H_0 prospectively.

Another Bayes factor is (BF_{01}) that provides evidence for the null hypothesis H_0 relative to the alternative hypothesis H_1, and it can be expressed as the inverse equation of (BF_{10})(Faulkenberry et al., 2020; Van Doorn et al., 2021).

Bayesian analysis offers credible intervals, which are "roughly analogous to a confidence interval"(Young, 2019). These intervals represent the ranges that contain a percentage of the posterior probability distribution for a parameter, typically set at 95%. For more explanation, A 95% credible interval, presents the range covering the central 95% of the posterior distribution for given the observed data, indicating that there is a 95% probability that the effect resides within this interval(Berkhout et al., 2023; Goss-Sampson, 2020; Young, 2019)

Kruschke(2010) and Young(2019) advocate for the application of Bayesian analysis in cognitive and behavioral research over traditional methodologies for several reasons. Firstly, Bayesian analysis offers flexibility in handling diverse data types. Secondly, it addresses the limitations associated with *p*-values and traditional methods by emphasizing the degree of evidence, which is a notable advantage. Additionally, Bayesian analysis effectively accounts for uncertainty by providing credible intervals that help enabling robust estimations and quantification of uncertainty. Furthermore, it fits the analysis of small sample sizes due to its sensitivity to prior knowledge, and it offers direct descriptions that enhance interpretability.

The Mann–Whitney U test is a non-parametric statistical method that employs a ranking approach to evaluate the difference between two groups. This test compares the data from the two groups as ranks to assess which group has lower or higher ranks. The Mann–Whitney U test is being used within Bayesian analysis as it is considered an alternative to the independent-samples t-test when the sample size is small or the data are non-normally distributed, or the data type is ordinal. It can be used also with continuous data; however, it will handle these data as rankings. It provides robustness that makes it a reliable choice for skewed data or data containing extreme values (Chechile, 2020; Chicco et al., 2025).

Kruschke(2021) and Young(2019) indicate that although the incorporation of prior knowledge is viewed as beneficial, with small sample sizes, they criticize this dependency on prior knowledge. Young(2019) offers several reasons for this criticism:

knowledge is derived from previous studies and each with its own experimental conditions, and that Bayesian inference is not a computational method, thus failing to achieve consistent results.

2.10 LITERATURE REVIEW SYNTHESIS

Wayfinding in research demonstrates many tasks, and these tasks are organized in a good taxonomy. However, other researchers argue that there is a missed category in the current taxonomy which is path-following task, depending on whether navigators possess prior survey knowledge about the environment surrounding an unfamiliar path.

To address this gap, the present study testing the gained spatial knowledge using a video with embedded VGLs that were reviewed for their effectiveness in spatial learning and simulates everyday tasks of passive learning, this methodology will give a chance to examine participants have pre-existing survey knowledge about broader areas and recruit participants overseas who don’t have any prior knowledge. To test the effect of the survey knowledge, literature demonstrates its impact on different tasks in wayfinding and how it affects the learning process. Additionally, the literature highlights the different tasks related to each type of spatial knowledge and they will be tested statistically through Bayesian analysis shown its compatibility with cognitive and behavioral science from previous studies.

3. METHODOLOGY

3.1 OVERVIEW

The study uses methodological framework to investigate whether wayfinding path-following task differs cognitively depending on the navigator's prior survey knowledge of the broader environment by examining the different types of spatial knowledge gained from a navigational video with embedded landmarks with a transparent and replicable account of the research process.

The overall framework, illustrated in Figure 3-1, includes participant recruitment, the main steps of the experiment, and data preparation for analysis, ultimately leading to the results.

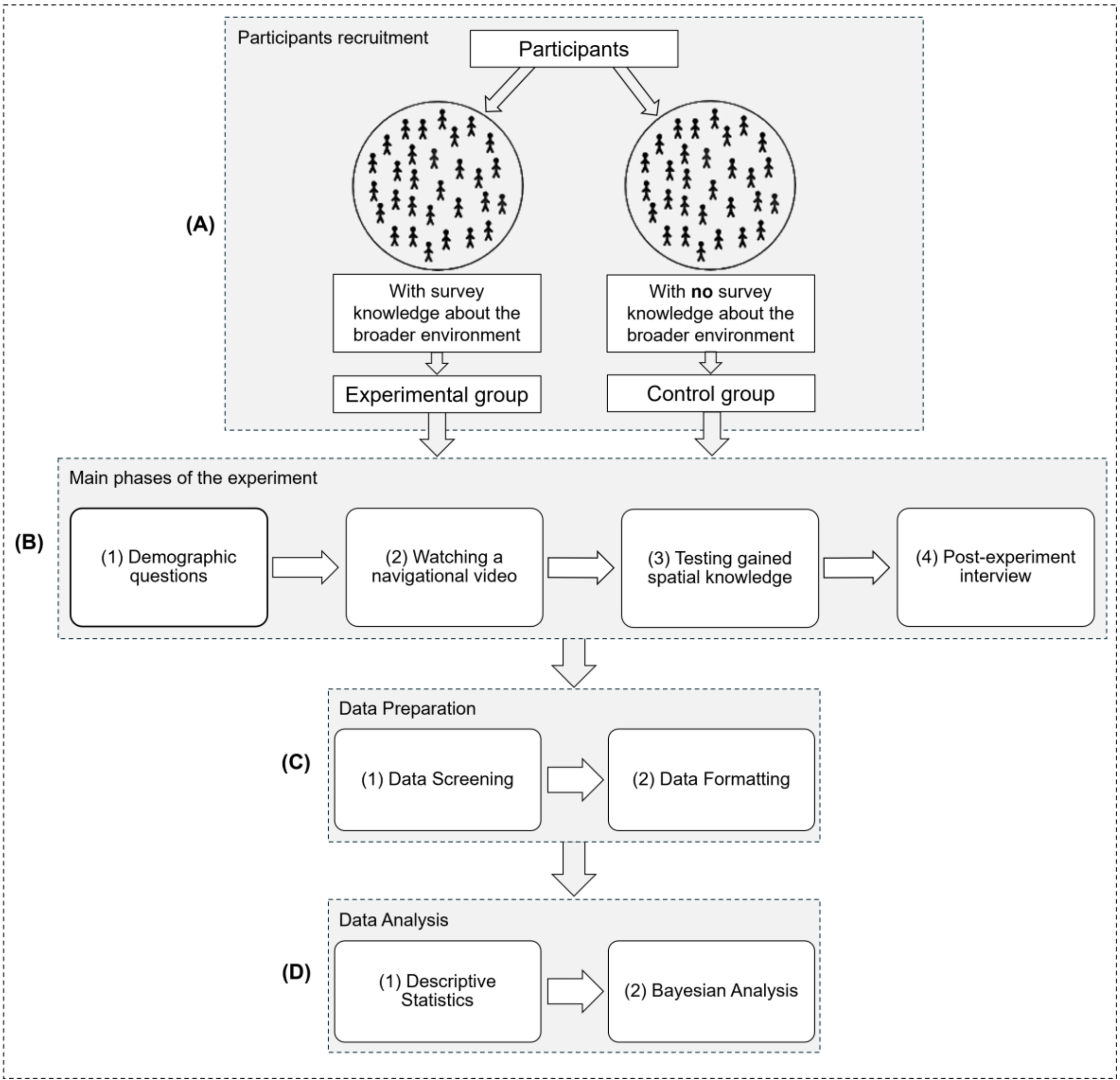

Figure 3-1 The overall methodological approach.

This chapter provides a detailed description of the study area and route design that the video was made based on them, then, online questionnaire. Subsequently, describing the variables and measures being employed to test each type of spatial knowledge. The procedure section explains the experimental conditions, the sequence of tasks.

Together, these sections provide a comprehensive overview of how the study was designed and implemented to test the proposed hypotheses.

3.2 RESEARCH DESIGN

This study investigates the impact of the existing survey knowledge that individuals have about surrounding areas of a navigation path on the acquired spatial knowledge from a first-person video with VGLs along unfamiliar route, employing an Experimental design with a between-subjects approach to examine the differences, Figure 3-1(A). The study features one independent variable, the level of spatial knowledge, which is categorized into two levels. The Experimental group possesses survey knowledge of the broader areas, whereas the Control group lacks such knowledge and only depends on the knowledge gained from the video, while The Experimental group has both.

Group differences are assessed using tasks targeting distinct forms of spatial knowledge: landmark knowledge (landmark identification task), route knowledge (landmark organization and route choice tasks), and survey knowledge (relative direction, distance estimation, camera-location awareness, camera-orientation, and layout identification tasks). The dependent variables are the scores (number of correct responses) obtained for each task separately.

3.3 PARTICIPANTS

The study involved 42 adults who met the inclusion criteria, with 21 individuals assigned to each group. The Experimental group comprised 12 males and 9 females, aged between 22 and 35 years, while the Control group included 10 males and 11 females, aged between 23 and 33 years. The proportions of various age groups and genders are intentionally balanced to prevent the predominance of any gender or age group.

All participants have backgrounds in geospatial science or architecture. Individuals represented various nationalities across both groups. An additional inclusion criterion was the level of spatial knowledge. The Control group consisted of individuals without any prior survey knowledge of the study area in Lisbon, whereas the Experimental group included those with substantial prior survey knowledge of Lisbon, thus only individuals who currently reside or have resided in Lisbon were included. Participants were recruited through the researcher's online social networks. The target population comprises adults with higher education in spatial disciplines, drawn from the researcher's international network.

3.4 STUDY AREA AND ROUTE DESIGN

3.4.1 AREA SELECTION

The study examines the impact of survey knowledge concerning areas outside the navigation route. Consequently, the primary criterion is that the area must be unfamiliar to ensure that all path segments and points are novel to participants and it is their first exposure, so everyone has the same baseline of knowledge. Therefore, participants from the experimental group were asked regarding their familiarity with the area. 'Campo de Ourique' was selected, Figure 3-2, due to its central location in Lisbon and its proximity to numerous well-known global landmarks. Additionally, it encompasses various types of local landmarks, including buildings, a church, statues, playgrounds, a market, and gardens, which contribute to the route's design (Steck & Mallot, 2000).

Figure 3-2 Study area in Lisbon, ‘Campo de Ourique’, is highlighted (dashed circle), indicating the spatial context in which the experiment was conducted.

3.4.2 ROUTE DESIGN

The route, Figure 3-3, is designed to include multiple route segments:10 straight line segments and one curved segment connected to one of the other 10 segments, and this number of is slightly above (7 ± 2), the optimal number of segments mentioned by Golledge (1992), this number of segments keeps a multiple decisions of turning left, or right, or continue straight forward across the route. The segments were selected to have different lengths, so it helps with distance estimation tasks.

The route was designed to incorporate distinct and easily identifiable features, to have between 9 and 11 local landmarks, consistent with previous studies. For example, Burte and Montello (2017) included 9 landmarks, Liu, Singh, Wunderlich, et al.(2022) included 11, and Manganelli (2016) included 10. Consequently, the actual number of landmarks was set at 10 to prevent excessive video length. The majority of local landmarks are selected to be on street conjunctions, 9 landmarks from the 10 (Steck & Mallot, 2000).

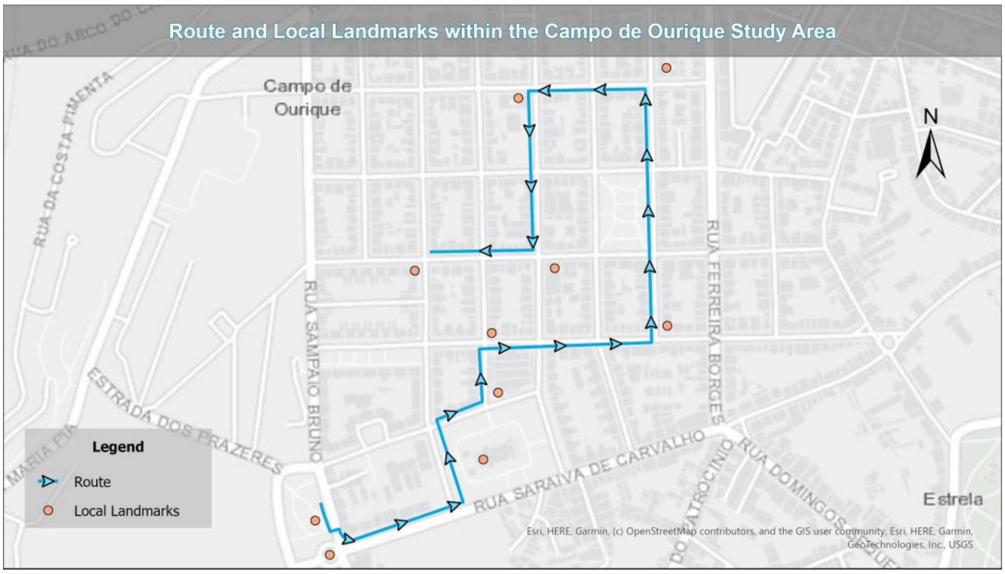

Figure 3-3 Experimental route (in cyan) and local landmarks (in orange) within the Campo de Ourique study area, used in the navigation task.

3.4.3 LOCAL LANDMARKS SELECTION

The selection of the landmarks was based on their uniqueness in space to act as reference points on the route and for example the selected set of landmarks, shown in Figure 3-4, have a playground, a statue, a church, a market, a café, other buildings.

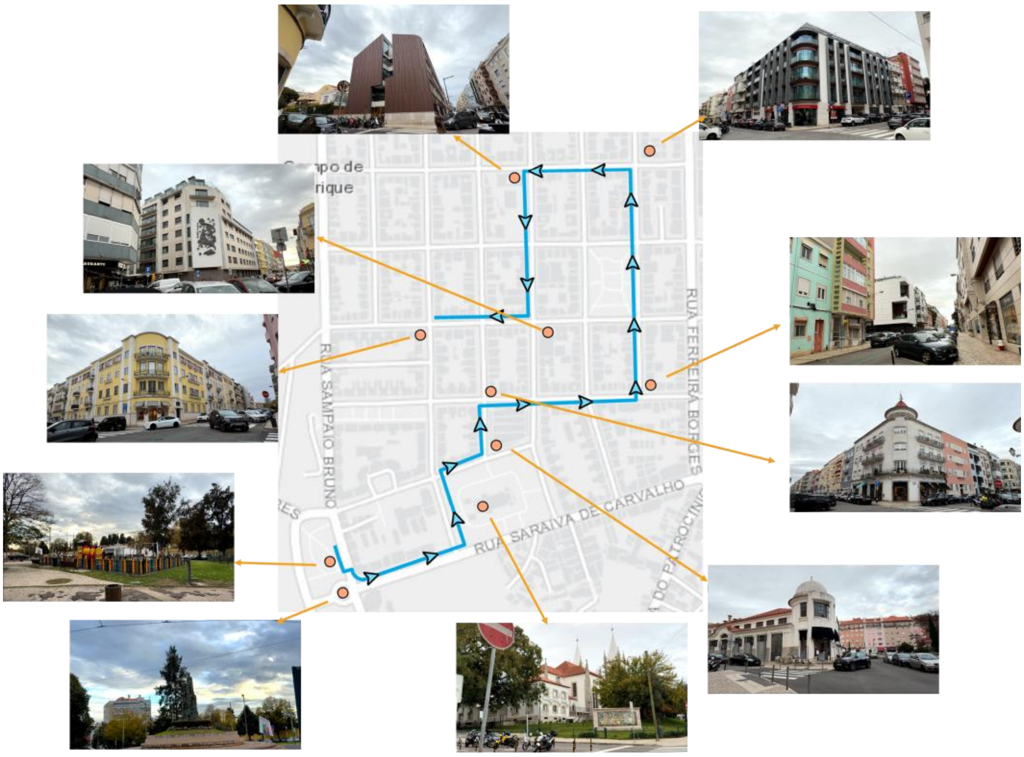

Figure 3-4 The figure displays the navigational route and the local landmarks with their pictures

3.4.4 GLOBAL LANDMARKS SELECTION

To study the effect of the survey knowledge in the nearby areas which refers to an understanding of the layout or the arrangement of an environment, a group of global landmarks were selected to be in the video so to make a frame of reference points distributed around the area of navigation in multiple directions(Steck & Mallot, 2000).

Figure 3-5 The location of the Campo de Ourique study area (dashed circle) in relation to surrounding Visual Ground Landmarks (VGLs)

Figure 3-5 presents a map of global landmarks intended for virtual representation in the video. These landmarks include a forested hill, the 25 de Abril Bridge, a railway, the Tagus River, and three statues located in Praça do Comércio and Marquês de Pombal squares, along with the prominent statue of the Sanctuary of Christ the King, labeled as numbers 2, 3, and 1 on the map, respectively. The scenes in Figure 3-6 depict these global landmarks from angles facing the study area 'Campo de Ourique'. These landmarks encompass not only point features but also linear, and surface features, supporting the formation of a mental representation of the surroundings. These landmarks were selected based on their familiarity and prominence in the touristic well-known areas of Lisbon.

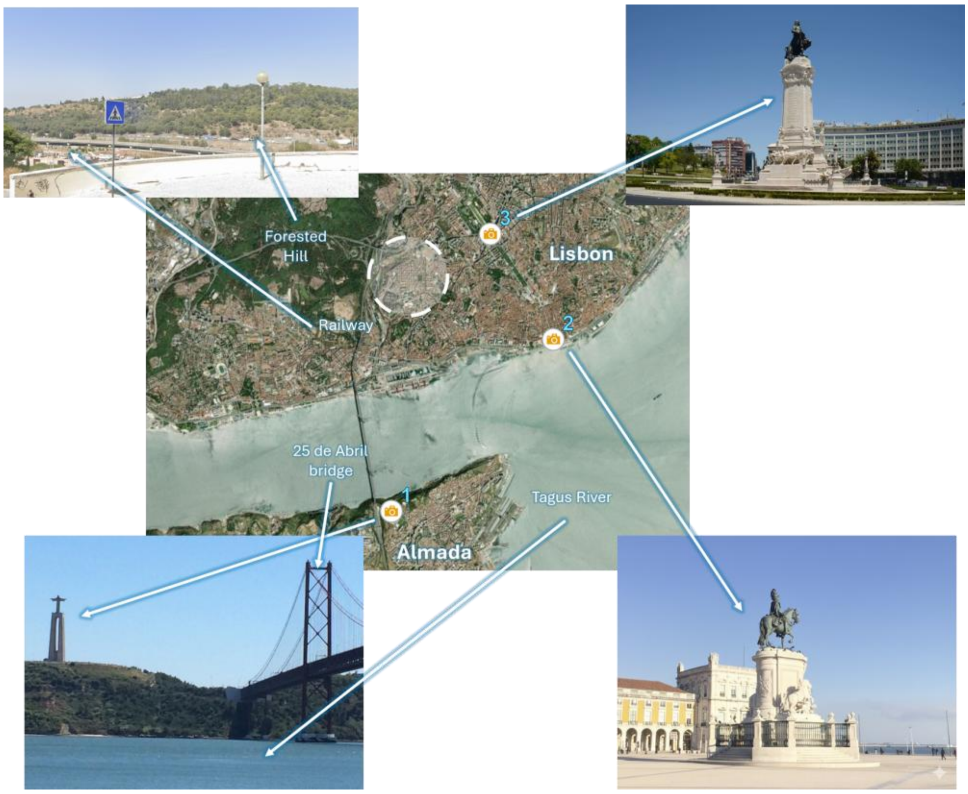

Figure 3-6 Pictures show real scenes for the global landmarks

To exhibit the selected landmarks in the video, a conversion process was undertaken whereby 2D images of global landmarks were transformed into visual graphics that will act as VGLs. The pictures of landmarks are with the angles facing the study area. This conversion was executed by Google Gemini, utilizing a prompt to render the landmark into a silhouetted 2D view at their angle of sight when seen from the route. The prompt was adjusted as necessary to ensure consistent outputs. For instance, Figure 3-7 illustrates one of the landmarks, the central statue in Praça do Comércio, and demonstrates how the actual image was converted into a VGL.

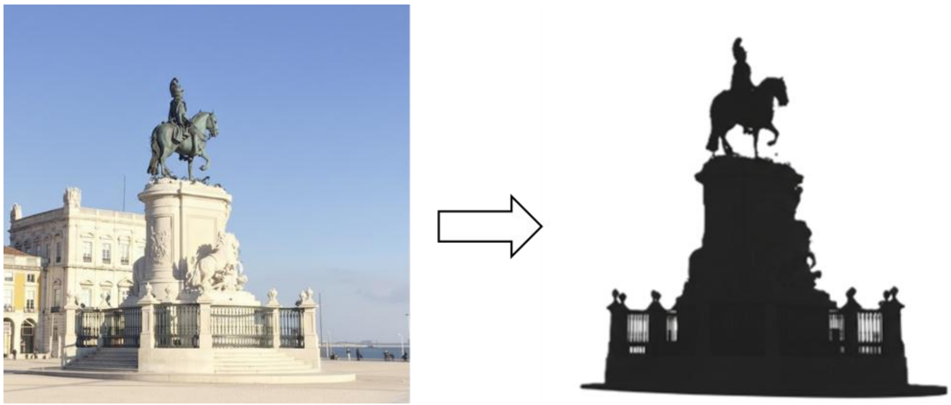

Figure 3-7 Central statue in Praça do Comércio before and after conversion to a 2D silhouette

3.5 MATERIALS AND APPARATUS

3.5.1 VIDEO WITH VGLS

This study provides an approach of testing the gained spatial knowledge from a navigational video showing virtual distant views.

The utilization of a video-based experiment is a suitable methodology for this study, given that the experiment involves two groups, one of which lacks spatial knowledge of Lisbon. The video format facilitates the recruitment of participants from outside Lisbon and simplifies the process of assembling large sample sizes by including former residents of Lisbon. Furthermore, it is economical method and allows for easy repetition of trials or testing. Additionally, the video simulates everyday tasks while participants passively observe the routes(Muffato et al., 2023).

Video-based approaches provide controlled testing condition as it has the same exposure to all participants, and they receive identical visual input and reduce exploration time as it doesn’t depend on body motion (Chang & Wang, 2010).

The video was recorded during daylight in Campo de Ourique. It is a first-person perspective video captured while walking. The recording was conducted in 4K resolution using a stabilizer.

During Video editing, the video accelerates to four times its original speed along straight segments to optimize its duration. In the literature, such as (Hegarty et al., 2006; Wen et al., 2011), videos typically have a duration of approximately 5 minutes, whereas the duration of the produced video is 5 minutes and 55 seconds.

(A) (B)

Figure 3-8 (A) the picture presents a local landmark from the video (B) the picture displays a VGL with its label "Marquês de Pombal"

The video has pauses and slightly zooms in on the ten local landmarks. Subsequently, the distant view behind the immediate scene, including VGLs, becomes visible.

To embed the VGLs into the video, after practically trying many methods, the method used is comparing the view in the video with the 2D map in ArcGIS pro. In Figure 3-8(B), the camera view was analyzed in comparison with the 2D map to ascertain the left and right boundaries. Subsequently, a line was drawn from the navigator's position, extending in length to encompass all global landmarks included within in the viewing angle of the camera. Additionally, a line was drawn from the observer's position to the global landmark as in Figure 3-9. Based on this the VGL with its label was added to the video like in in Figure 3-8(B).

The video and materials of VGLs are open source, enabling the replication of video creation (Appendix A).

Figure 3-9 Identifying the location of VGLs in the screen

The system of the VGLs used in (Liu, Singh, Wunderlich, et al., 2022) employs a continuous display approach, ensuring that they remain visible to the observer as long as they are being observed. Consequently, at all local landmarks, the VGLs become visible immediately after the landmarks are shown after pausing the video and each VGL is presented at least twice after different two local landmarks. This design allows the VGLs to be embedded directly after the display of local landmarks, thereby reducing pause time.

3.5.2 ONLINE QUISTINAIRE

A structured online questionnaire was administered via the LimeSurvey platform. The digital questionnaire comprised yes/no questions, multiple-choice, ranking, and short-response items, and participants were allowed to complete it without a time constraint. All questions were mandatory to avoid missed answers, and the dependent variables were measured using multiple-choice questions (MCQs) to prevent the occurrence of invalid responses that may arise from text-based answers. The images and materials for the VGLs in the questionnaire are open source, facilitating the recreation of the form (Appendix A).

3.6 VARIABLES AND MEASURES USED

To examine variations in acquired spatial knowledge, each type of knowledge is associated with a set of questions for tasks that reflect the dependent variables of the study. Each task has a score of correct answers based on the number questions per task.

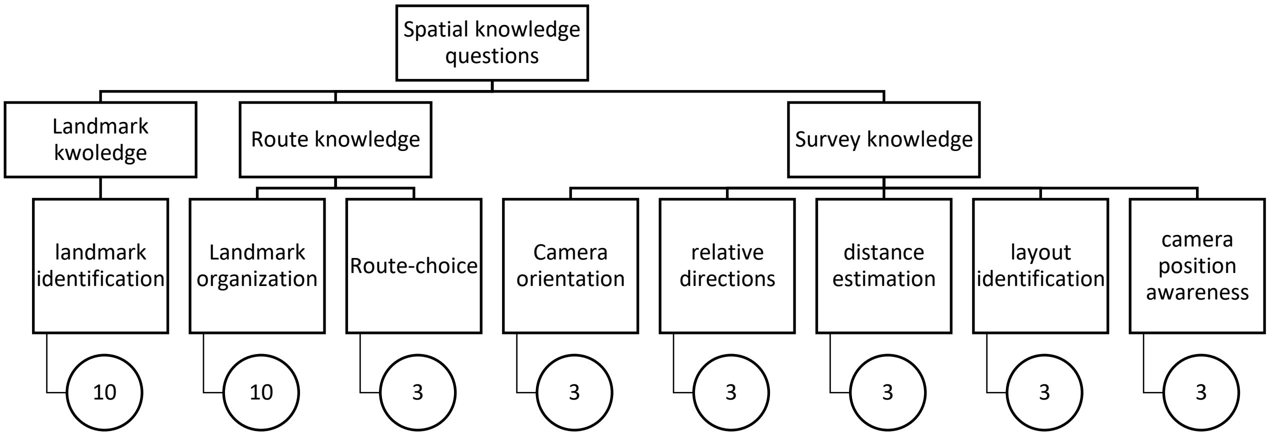

Figure 3-10. The diagram shows the different tasks (in squares) in the questionnaire related to each type of spatial knowledge, while the number of the questions are illustrated in circles

3.6.1 LANDMARK KNOWLEDGE

Landmark knowledge is assessed through a landmark identification task consisting of 10 yes/no questions. A correct response is awarded a score of 1, while an incorrect response receives a score of 0, resulting in a maximum possible score of 10.

3.6.2 ROUTE KNOWLEDGE

The assessment of route knowledge comprises 13 questions, which are divided into two tasks: landmark organization and route-choice.

The first task requires participants to organize the 10 landmarks observed along the route, with a maximum score of 10 for this question. The scoring of the landmark organization task is based on the Levenshtein algorithm. Initially, the codes from LimeSurvey, which consist of four characters, were converted into strings of a single character, as the Levenshtein algorithm is sensitive to the length of the concatenated string(Yujian & Bo, 2007). Subsequently, the Levenshtein distance was calculated and verified, where a score of 0 indicates a perfect order and a score of 10 represents the least order. The results were then normalized to a scale of 10 in another column, with 10 being the maximum value and 0 indicating no correct ordering (Appendix A).

The second task is route choice, where participants were required to choose the routes or directions they followed at three specific landmarks. Consequently, the score for this task is based on a total of 3 points.

3.6.3 SURVEY KNOWLEDGE

The survey comprises 15 questions, organized into five distinct tasks, with each task containing three questions. Consequently, the score allocated to each task is three. These skills include relative directions, distance estimation, layout identification, camera-location awareness, and camera-orientation (instead of body-location and body-orientation awareness in other studies without a person navigating instead of using videos), the score for all tasks is determined by the number of correct answers.

3.7 PROCEDURE

3.7.1 EXPERIMENTAL CONDITIONS

The study was conducted online under supervision using Microsoft Teams video conferencing software. Participants were instructed to share their screens while completing the tasks and to utilize incognito mode to ensure their privacy. The study was administered through the LimeSurvey online platform, and the entire experiment required approximately 30 to 40 minutes to complete, and main phases of the test are demonstrated in Figure 3-1(B).

Participants in both groups, Figure 3-1(A), were subjected to similar conditions. The cohorts comprised young adults with similar age ranges in the two groups and balanced gender representation, all possessing a background in geospatial sciences, and a maintained diversity balance across the two groups.

To ensure equivalent conditions, participants in the control group were chosen because they had no previous knowledge of Lisbon, whereas those in the experimental group were chosen for their high survey knowledge by living in Lisbon. Neither group was informed about the spatial context of the study area, including whether it is in Lisbon.

3.7.2 DEMOGRAPHIC QUESTIONS

The questionnaire began with demographic questions about age, gender, country of origin, academic background, and familiarity with Lisbon. These questions were used to determine participants’ eligibility according to the study’s inclusion criteria and to determine the characteristics required for subsequent participants, such as ensuring an equal distribution of individuals across groups, genders, and other relevant categories.

The inquiry regarding familiarity with Lisbon serves as an initial screening mechanism prior to viewing the video. Participants who indicated a lack of prior knowledge about Lisbon were assigned to the control group.

3.7.3 WATCHING A NAVIGATIONAL VIDEO

Prior to viewing the navigational video, participants were instructed as follows: Carefully watch the navigation video, to maximize attentional engagement, participants were informed that the video is the most important phase of the study. To not use any external resources (e.g., notes, drawings, digital sketches, maps). Once the questionnaire has started, the video may not be revisited.

Prior to the start of the video, additional notes were shared with participants to clarify the content of the video and to outline the questions they would be expected to answer following viewing step. These notes were provided based on feedback from participants on the pilot test and their performance regarding their comments.

Notes concerning landmarks: The video will pause at significant landmarks. Within the video, viewers will observe distant silhouetted two-dimensional view from the videographer's location, as exemplified in Figure 3-11. This serves to illustrate what extends beyond the immediate scene at the moment of capture. The sizes of the landmarks may vary depending on the position on the route, corresponding to their distance from the photographer.

Figure 3-11 Example for how the distance view is shown in the video

Additionally, they were instructed to freely pause, speed up, slow down, and to watch the video twice, mimicking (Hegarty et al., 2006; Muffato et al., 2023), the first time to let them freely explore what in the video and get familiar with the route and the VGLs, then the second time to spatial learning.

The final clarification indicated that participants would be questioned regarding landmarks, directions, and the overall spatial knowledge acquired from the actual route. (Appendix A)

Prior to advancing to the next phase, an additional inquiry was asked to filter participants residing in Lisbon. This was done to ascertain whether they were exposed to the route depicted in the navigation video. Participants who were either familiar with the route or uncertain about their familiarity were excluded from completing the test.

To maintain participants’ attention and engagement, the instructions emphasized that this step was particularly important. Participants were also allowed to interact with the video by adjusting the playback speed and using the timeline slider to navigate through the content. This flexibility was intended to reduce potential boredom during slower segments and sustain overall engagement.

3.7.4 TESTING THE GAINED SPATIAL KNOWLEDGE

During this phase, the questions and answers were randomized in a way that each question was independent and did not influence the others.

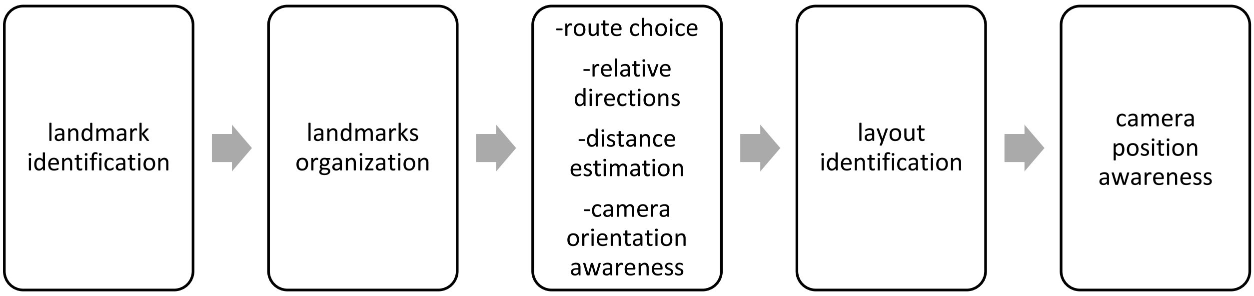

Figure 3-12 Sequence of the questions with respect to randomization

The sequence of questions, Figure 3-12, begins with the identification of landmarks, followed by the organization of these landmarks. Subsequently, randomized questions about (route choice, relative direction, distance estimation, camera orientation awareness) are presented, leading to the identification of layout and concluding with an awareness of camera position.

Landmark identification:

This task comprises a series of yes/no questions, five questions for landmarks appeared along the route, while the remaining five serve as distractor items, as inspired by the study (Wen et al., 2011). Figure 3-13 shows two landmarks, one of which is visible on the route while the other is not. The landmark identification questions were consistently presented at the beginning of the questionnaire, with the sequence of the ten questions being randomized.

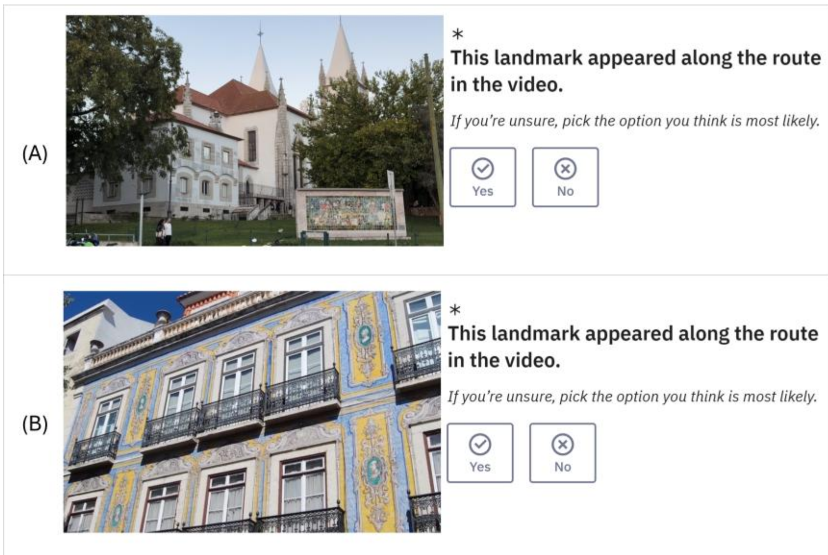

Figure 3-13 (A) an example of a landmark that was featured in the video (B) represents a landmark that did not appear in the video.

Landmark organization:

In the task, participants were asked to organize all the landmarks that appeared in the navigational video, by sorting them ascending as shown in Figure 3-14. As it reveals all ten correct landmarks, it consistently appears after the identification task and before the subsequent tasks, and the landmarks presented randomly before being sorted by participants.

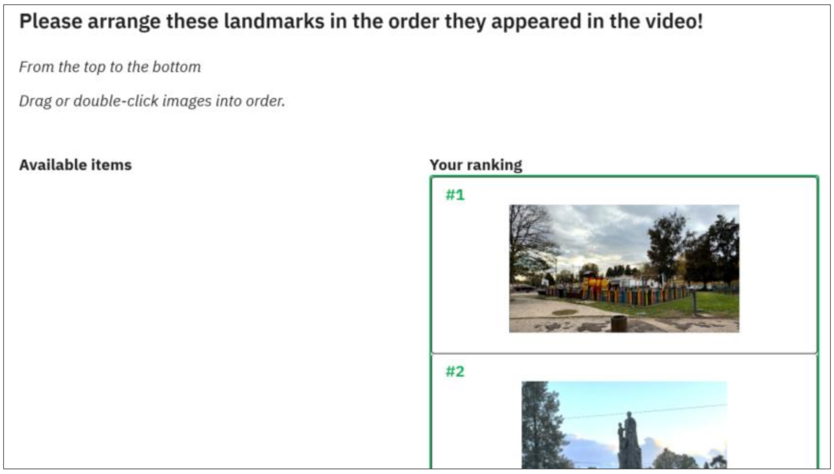

Figure 3-14 A snapshot showing the question

Route choice:

In this question, participants were provided with images accompanied by instructions pertaining to the actions undertaken at these landmarks as depicted in the recorded video of the route.

Figure 3-15 Sample of route choice questions with the correct answer marked in green

Relative direction:

In the tasks involving relative direction, participants were required to give the direction from one landmark to another through three distinct questions, Figure 3-16: the question in the lower image is to provide the direction between two consecutive landmarks; upper-right question is to offer two directions to reach the second landmark; and upper-left one to describe two directions in the reverse order.

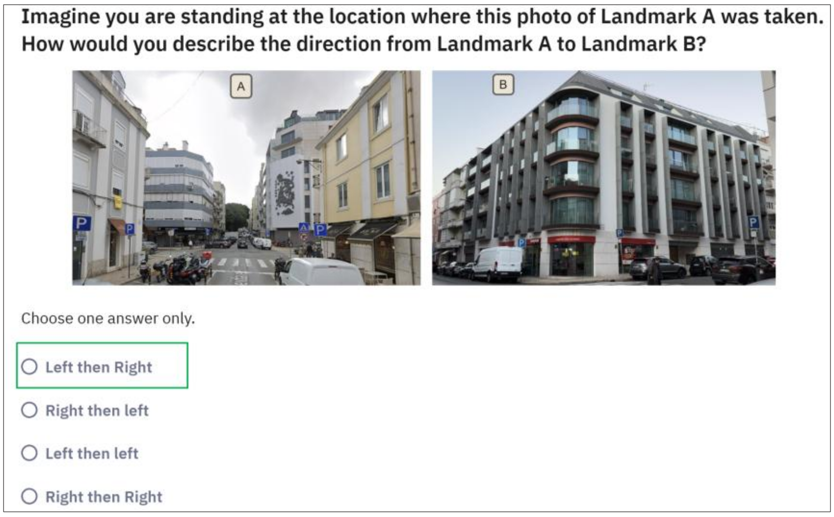

Figure 3-16 Sample of relative directions question with correct answer market in green

Distance estimation:

Distance estimation was assessed through three specific questions: first, participants were asked to estimate the shortest distance among three landmarks that appeared along the route; second, they were tasked with estimating the closest landmark in straight-line distance to a specified landmark; and third, they were required to determine which of the three landmarks was closest in straight-line distance to the final landmark.

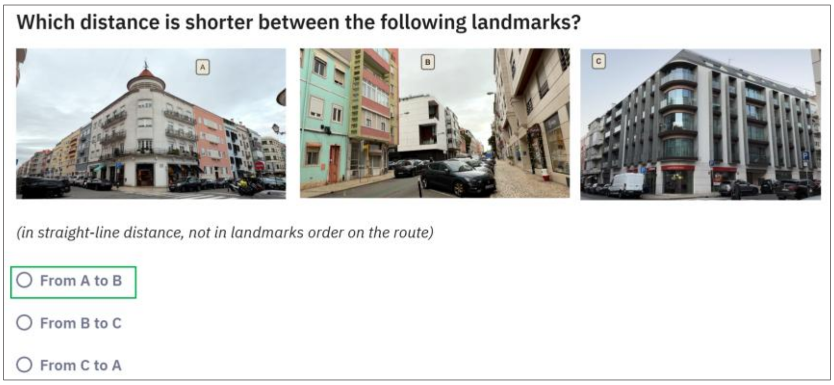

Figure 3-17 Sample of distance estimation questions with correct answer market in green

Camera Orientation:

In this task, participants were instructed to visualize themselves standing at a location, looking at one of the local landmarks, and subsequently to envision the orientation towards a third landmark. They selected the direction using a pizza graph, which represented a compass divided into eight segments. The landmarks in this task were strategically chosen to prevent any direction from being too close to the boundary separating the eight segments.

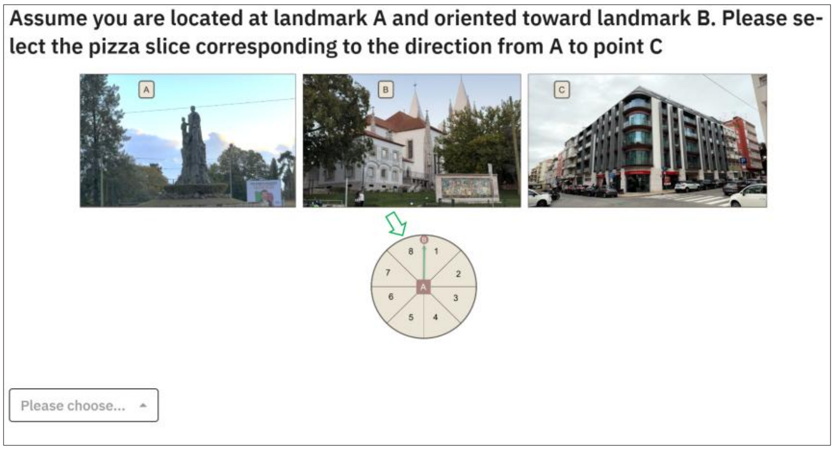

Figure 3-18 Sample of camera orientation questions with correct answer at 8

Layout identification:

The layout identification task was evaluated through three questions. The first two questions were on specific segments of the route and were presented in a randomized order. In contrast, the third question addressed the overall route and was consistently presented as the final question in this task, Figure 3-19. The answers were intentionally designed to contain errors in different sections that were not present in the first two questions.

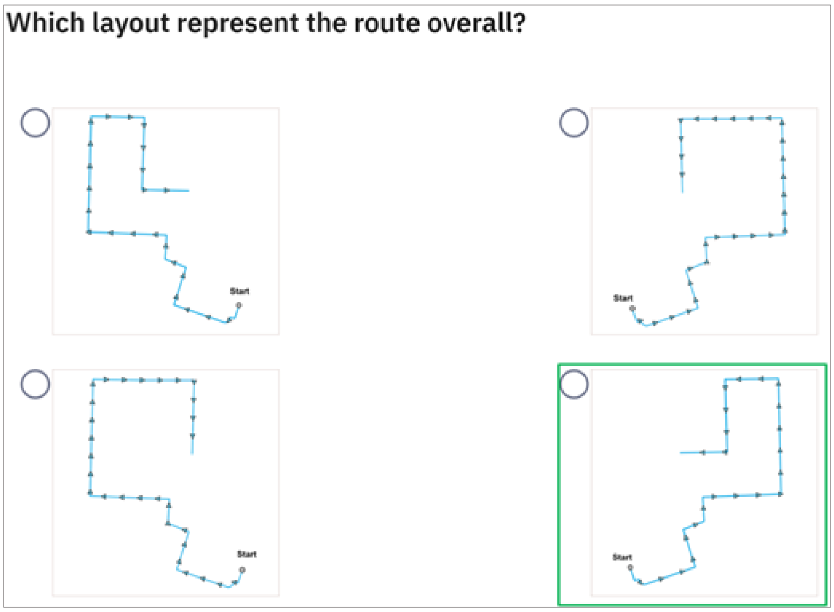

Figure 3-19 Sample of layout identification questions with correct answer marked in green

Camera location awareness:

This task was assessed using three questions that consistently followed the layout identification questions, as these questions disclose the correct layout. The questions presented an image from a segment of the route depicted in the video and subsequently required the identification of that segment's location within the route.

Figure 3-20 Sample of camera location awareness questions with correct answer marked in green

3.7.5 POST-EXPERIMENT INTERVIEW

Subsequently, participants in the experimental group were asked if they recognized the routes, landmarks, or areas shown in the video. This step resulted in the exclusion of two individuals who had only casually visited Lisbon, as they lacked sufficient knowledge of global landmarks. Additionally, another individual was excluded from the data because he/she was familiar with the route.

Most participants in both groups emphasized the significance of the VGLs in orientation, while few of them mentioned that they were distracted by the VGLs.

3.8 OTHER EXPERIMENTAL DESIGN CONCEPTS

3.8.1 RELIABILITY

Reliability refers to good quality of the results and handling random errors by adding more items for measurement (Bannigan & Watson, 2009; Golafshani, 2015), so each task has at least 3 questions to avoid the effect of these random error.

3.8.2 BLINDING

The study was based on a single blinding; Individuals participated in a blinded manner and were assigned to groups based on their familiarity with Lisbon and the "Campo de Ourique" area. They were unaware of their group assignments prior to participation.

To avoid observer bias, standardized instructions were written to ensure uniformity in the information provided to all participants. This approach prevents the observer (the researcher) from over-explaining or under-explaining, as verbal instructions may be biased and potentially influence outcomes due to the observer's knowledge of the participants assigned groups.

3.9 SOFTWARE/TOOLS USED

Microsoft Excel and JASP were utilized for the preparation and analysis of data. Clipchamp was employed for video production, ArcGIS Pro for map creation, and Gemini for the creation of silhouetted VGLs. LimeSurvey was used to design the form.

3.10 CHOOSING STATISTICAL ANALYSIS

The analysis is based on task score, calculated as the total number of correct responses per task. These aggregated numerical scores serve as the primary dependent variables for each task for hypothesis testing and group comparisons.

To examine differences between groups, a Bayesian Mann–Whitney U test was used. This non-parametric test for independent samples, is utilized due to the small sample size of 21 participants per group (Chechile, 2020; Goss-Sampson, 2020; Van Doorn et al., 2021). Additionally, the Mann-Whitney U test is also particularly suitable for small sample sizes and is applicable to any data distribution, as it does not assume normality (Chicco et al., 2025).

3.11 DATA PREPARATION

This data preparation part, Figure 3-1(C), aims to present the process by which raw data, obtained from the online form, is transformed into results. The raw data were collected via LimeSurvey and necessitated several preprocessing steps prior to analysis to ensure consistency and comparability across participants.

3.11.1 DATA CLEANING AND SCREENING

The initial step involves data screening for completeness. This process is conducted using LimeSurvey, from which I downloaded the complete responses, totaling 48 out of 58. As all questions were mandatory, there are no missing values in the completed attempts.

The second step of screening includes the removal of invalid complete responses. This includes 1 trial response, responses from participants whose criteria are not compatible with the rest of the participants, responses from 2 participants lacking a GIS background, and responses from 3 participants who demonstrated insufficient knowledge of global landmarks depicted in the video.

3.11.2 DATA FORMATTING

In the third step, all response codes were categorized as either true or false, with 0 representing incorrect answers and 1 representing correct answers. The total number of correct responses constitutes the score for each task, with calculations performed using Microsoft Excel. However, the landmark organization task employs an alternative method, utilizing the Levenshtein distance to determine the grade based on the sequence.

3.12 PILOT TESTING

A testing phase was conducted with 7 participants using both Google Forms and LimeSurvey to determine the most effective method for presenting questions and to assess the clarity of the questions for participants. Based on this phase, questions about camera orientation were made using a pizza diagram rather than numerical angles because participants expressed greater comfort responding to the pizza diagram compared to numerical representations.

In response to this phase, I transitioned the work to Limesurvey, which facilitated the randomization of landmarks organization questions. Instructions were added before participants viewing the video based on feedback, addressing their inquiries regarding what to observe in the video and what questions they might encounter afterward.

Furthermore, the visual guidance landmarks (VGLs) were explained before the video viewing, rather than during, to minimize text within the video and to enable participants to concentrate on the route and landmarks without interruptions for reading text. This step was crucial in utilizing VGLs instead of visible global landmarks.

3.13 ETHICAL CONSIDERATIONS

Participation in the study is voluntary. The study involves minimal risk, limited to standard computer use, and does not provide personal benefits. Participants are instructed to use their web browser in private or incognito mode to ensure their privacy while opening the video on YouTube. No personally identifiable information was collected, and all responses were recorded anonymously.

4. RESULTS

This chapter presents the results from two groups concerning tasks related to each type of spatial knowledge. Descriptive statistics were used to summarize the outcomes for each group. Subsequently, statistical tests were conducted to ascertain whether the results indicate the superiority of the Experimental group as hypothesized in this study. Hence, the tests examined whether the results support the alternative hypothesis (H_+), suggesting (Experimental > Control), or if they provide evidence for the null hypothesis(H_0). The conditions and selected options in JASP of the tests are demonstrated in Appendix A. The interpretation of Bayesian analysis results is primarily based on the classification framework of (Goss-Sampson, 2020)and is further supported by the works of (Berkhout et al., 2023; Faulkenberry et al., 2020; Van Doorn et al., 2021).

4.1 LANDMARK KNOWLEDGE TASK

4.1.1 LANDMARK IDENTIFICATION

DESCRIPTIVE STATISTICS

Table 1 A descriptive analysis of the total correct responses from both the control and Experimental groups in the landmark identification task

	Landmarks_Identification	
	Experimental	Control
Mode	10	9
Minimum	8	8
Maximum	10	10
25th percentile	9	9
50th percentile	10	9
75th percentile	10	10

Table 1 presents a summary of the total correct responses to 10 questions concerning landmark identification. The table illustrates high scores across the control and experimental groups. Both groups achieved from 8–10 range of scores, as well as identical 25th and 75th percentiles (9 and 10) respectively, Despite the experimental group had the perfect score of 10 as a mode and median (50th percentiles), the median and mode of the control group is 9, which is slightly smaller than the perfect score.

Figure 4-1 demonstrates that the Landmarks Identification scores are predominantly concentrated at high values, specifically within the range of 8 to 10. In the Control group, most scores are 9 and 10, with a smaller number of scores at 8. The Experimental group shows skewness towards higher values, as most scores reach the maximum value of 10, with fewer scores at 8 and 9.

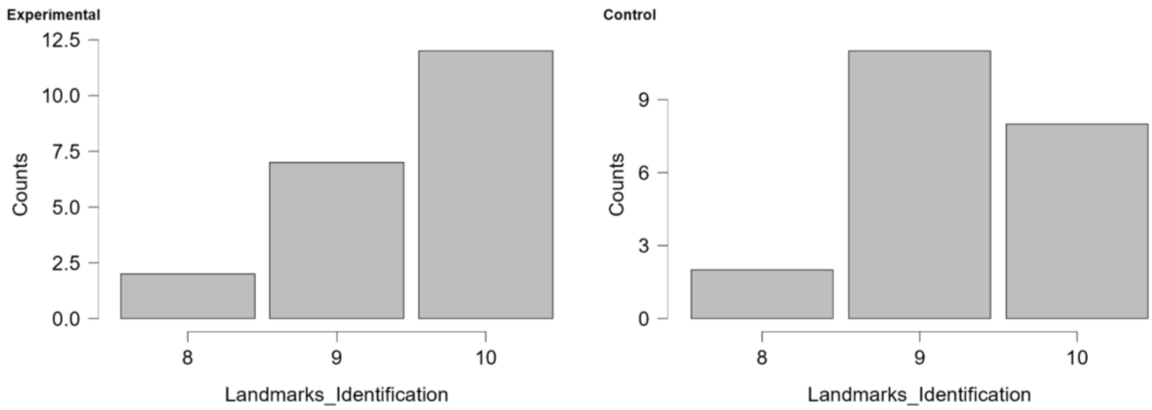

Figure 4-1 The distribution of total correct responses for Landmarks Identification task for both the control and Experimental groups.

STATISTICAL ANALYSIS

The Bayesian Mann-Whitney U test was employed to statistically determine whether the Experimental group could identify a greater number of landmarks than the Control group. Table 2 presents the Bayes factor value (BF_{+0} = 0.632).

Table 2 Results of Bayesian Mann-Whitney U Test of the landmark identification task

	BF_{+0}	W	Rhat
Landmarks_Identification	0.632	258.5	1.000

In Figure 4-2, The graph illustrate the probability mass of the prior and posterior density is above 0, and there is a 95% probability that the true value of δ lies within the range from [0.017, 0.866], with the median value of 0.300 that represents the center of the posterior probability mass. The Bayes factors are shown in the upper left of the figure (BF_{+0} =0.632, BF_{0+}=1.583). In the upper center, the pizza plot illustrates the comparative likelihood of the data under (H_+) and (H_0), with the probability distribution of the data under (H_0) being slightly more dominant.

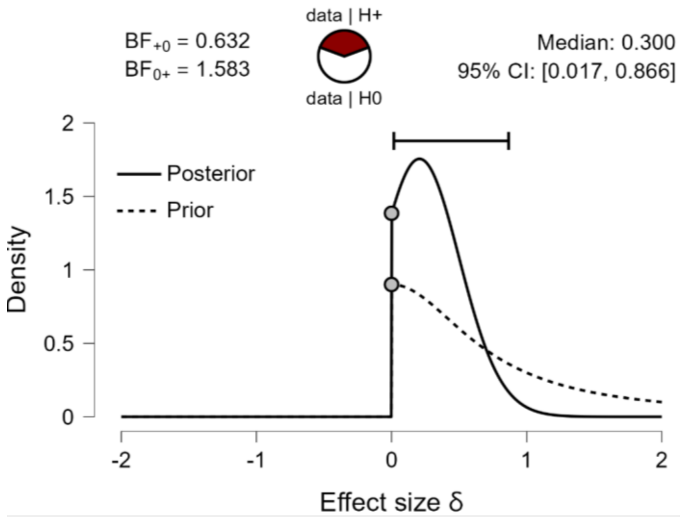

Figure 4-2 prior and posterior probability distribution of the score of correct answers in the landmark identification task

4.2 ROUTE KNOWLEDGE TASKS

4.2.1 LANDMARK ORGANIZATION

DESCRIPTIVE ANALYSIS

Table 3 summarizes the landmark organization scores for both groups: for the Control group, the values showed a moderate spread. The mode and the median (50th percentile) are both 5, which reveals the most frequent score, at least 50% of the participants achieved it. Scores lie in the range from 3 to 10, The percentile values are 5 at the 25th percentile and 8 at the 75th percentile. In the Experimental group, the mode was 8 and the median was 6, indicating higher scores compared to the Control group. Values ranged from 4 to 10, showing similar values at the 25th and 75th percentiles: 5 and 8, respectively, indicating a similar spread with the Control group but with clusters around higher values.

Table 3 Descriptive analysis of the total correct responses from both the Control and Experimental groups in the landmark organization task

	Landmark_Organization	
	Control	Experimental
Mode	5	8
Minimum	3	4
Maximum	10	10
25th percentile	5	5

	Landmark_Organization	
	Control	Experimental
50th percentile	5	6
75th percentile	8	8

The histograms, Figure 4-3, show the distributions of landmark organization scores for each group. In the Control group, scores are dense at 5 with fewer frequencies for the rest of values. In parallel, the Experimental group, the distribution shifts a bit toward higher values, with the most frequent scores at 6 and 8.

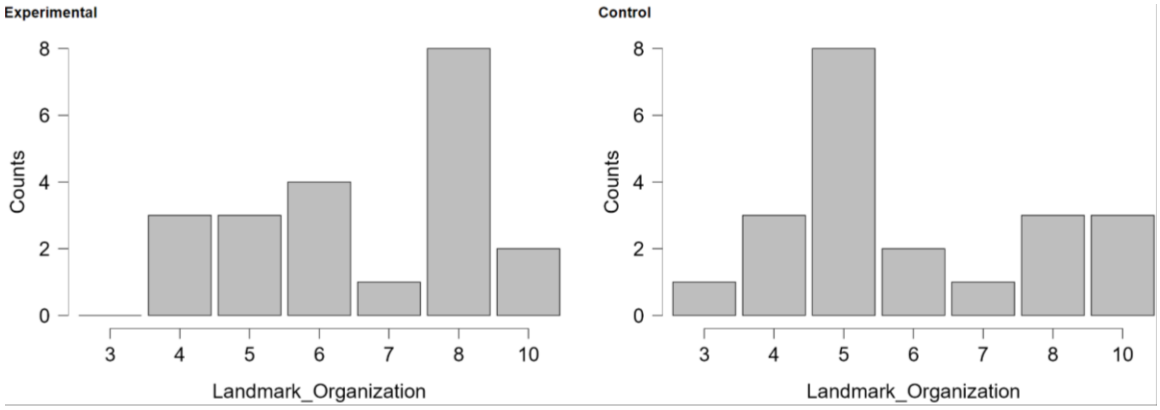

Figure 4-3 Data distribution of the summation of the correct answers for both groups for the landmark organization task

STATISTICAL ANALYSIS

The Bayesian analysis conducted for Landmark Organization indicates a Bayes factor value of $BF_{+0} = 0.757$.

Table 4. Results of Bayesian mann-whitney test of the landmark organization task

	BF_{+0}	W	Rhat
Landmark_Organization	0.757	269.0	1.000

The prior and posterior distributions of the probability have their mass above 0, and the 95% credible interval [0.020,0.866] and a posterior median of 0.317 with Bayes factor $BF_{+0} = 0.757$ and $BF_{0+} = 1.32$. The circular scale (pizza graph) illustrates the likelihood of the data under (H_+) and (H_0), with the probability distribution shows no dominant difference.

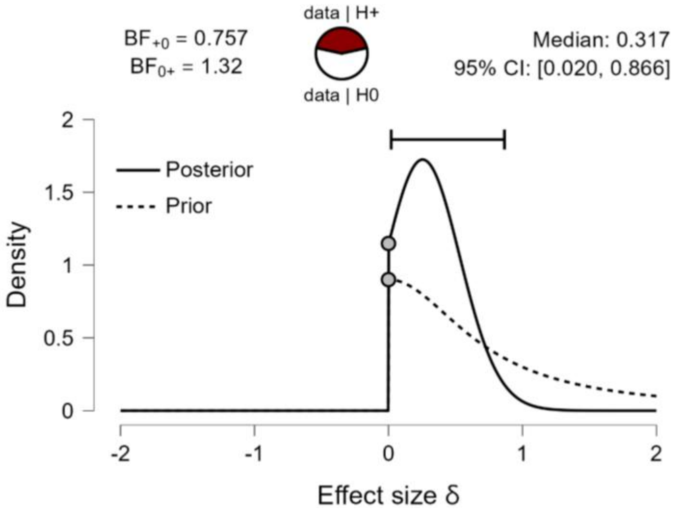

Figure 4-4 prior and posterior probability distribution of the score of correct answers in the landmark's organization task

4.2.2 ROUTE CHOICE

DESCRIPTIVE ANALYSIS

In Table 5, the route choice scores for the Control group clustered at higher values of 2 and 3, where 2 is the mode and the median (50th percentile) at the same time which indicates that at least half of participants tend to make 1 mistake among the three questions, with value of 2 (25th percentile) and 3 (75th percentile). In the Experimental group, the mode and the median (50th percentile) are also 2, showing similar performance. Scores ranged from 1 to 3, showing slightly higher scores. The 25th percentile is 1 and the 75th percentile is 3.

Table 5 Descriptive analysis of the total correct responses from both the Control and Experimental groups in the route choice task

	Route_Choice	
	Control	Experimental
Mode	2	2
Minimum	0	1
Maximum	3	3
25th percentile	2	1
50th percentile	2	2
75th percentile	3	3

The histograms, in Figure 4-5, show very similar distribution of the Route Choice score across the two groups. In the Control group, scores are clustered at 2, with many participants also scored 3 (the perfect score), and a small number of low scores of 0 and 1. In the Experimental group, scores are nearly identical, showing at 2 and 3, with a bit lower value at the score of 1.

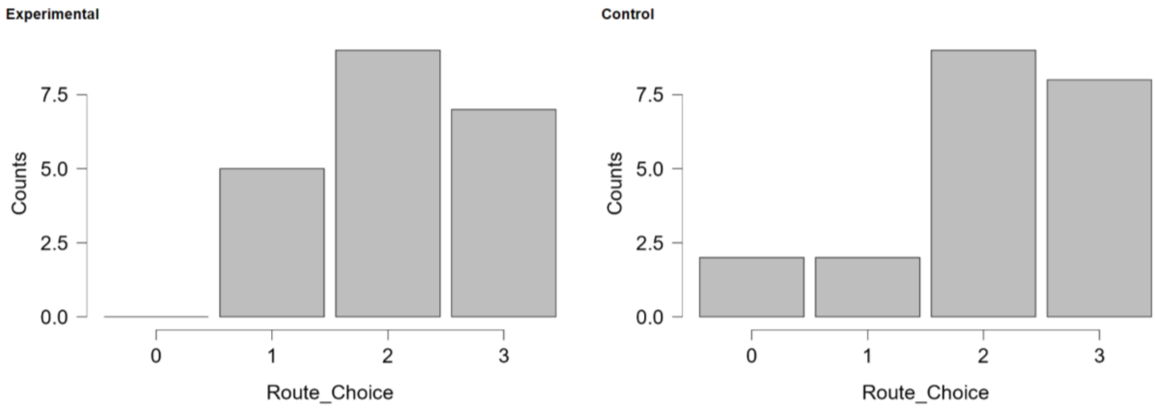

Figure 4-5 Data distribution of the summation of the correct answers for both groups for the route choice task

STATISTICAL ANALYSIS

Th Bayesian analysis presents Bayes factor BF_{+0} = 0.312.

Table 6 Results of Bayesian mann-whitney test of the route choice task

	BF_{+0}	W	Rhat
Route_Choice	0.312	210.5	1.000

The prior and posterior plot for Route Choice illustrates a small positive effect above zero, with a posterior median of 0.187 with the 95% credible interval of [0.008,0.653]. the Bayes factors are (BF_{+0} = 0.312) and (BF_{0+} = 3.209). The pizza graph shows dominant probability for the null hypothesis(H_0).

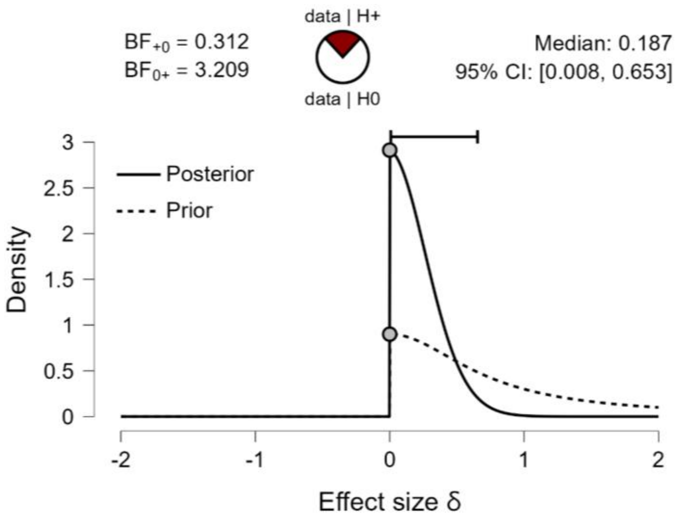

Figure 4-6 prior and posterior probability distribution of the score of correct answers in the route choice task

4.3 SURVEY KNOWLEDGE TASKS

4.3.1 RELATIVE DIRECTION

DESCRIPTIVE ANALYSIS

Relative direction task scores, shown in Table 7, in the Control group, the mode and the median (50th percentile) are 0, and scores ranged from 0 to 2, with a value of 0 at the 25th percentile and the 75th percentile was 1, showing a tendency of achieving low scores. Concurrently, the Experimental group show intensity at the value of 1, which is simultaneously the mode and the median (50th percentile). Scores ranged from 0 to 3, showing a broader spread compared with the Control group with values of 0 (25th percentile) and 2 (75th percentile), showing tendency toward higher scores.

Table 7 Descriptive analysis of the total correct responses from both the Control and Experimental groups in the relative direction task

	Relative_direction	
	Control	Experimental
Mode	0	1
Minimum	0	0
Maximum	2	3
25th percentile	0	0
50th percentile	0	1
75th percentile	1	2

The histograms show different Relative Direction score distributions across groups. In the Control group, scores are heavily concentrated at 0 and 1, with very few higher scores, indicating generally low relative performance direction. In the Experimental group, scores are more evenly distributed across 0, 1, and 2, with some participants reaching 3, indicating higher and more varied performance. Overall, the Experimental group demonstrates better relative direction performance than the Control group.

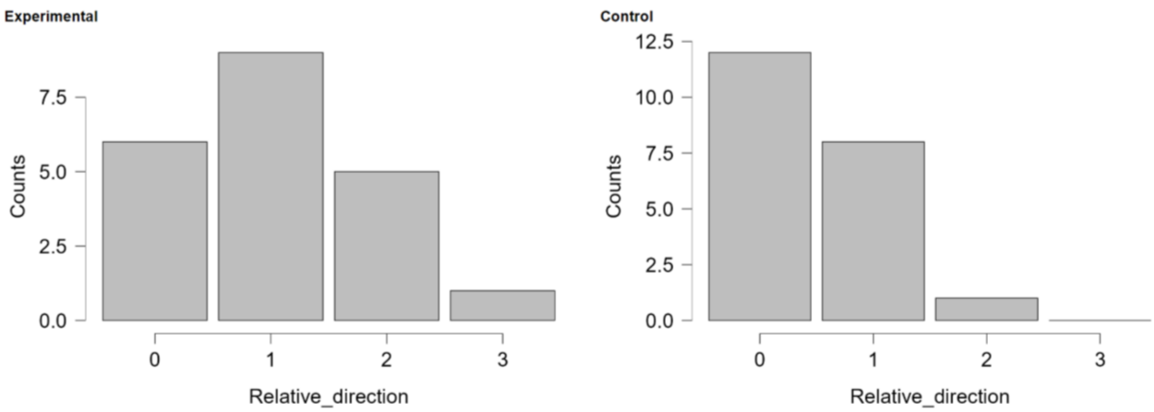

Figure 4-7 Data distribution of the summation of the correct answers for both groups for the Relative Direction task

STATISTICAL ANALYSIS

the Bayesian analysis indicates a Bayes factor BF_{+0} = 2.666.

Table 8 Results of Bayesian mann-whitney test of the relative direction task

	BF_{+0}	W	Rhat
Relative_direction	2.666	303.5	1.000

The prior–posterior distributions for Relative Direction task indicate a positive posterior distribution with a median of 0.545, accompanied with a 95% credible interval ranging from [0.063, 1.196]. The Bayes factors are reported as BF_{+0} = 2.666 and BF_{0+} = 0.375. The pizza scale demonstrates a dominant probability under the alternative hypothesis (H_+)

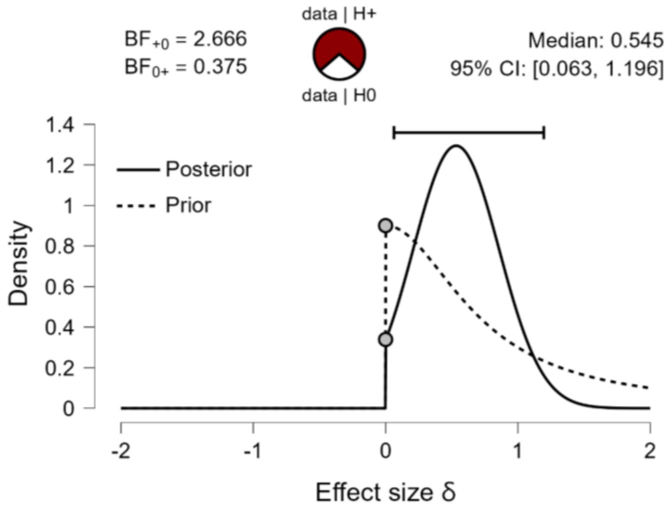

Figure 4-8 prior and posterior probability distribution of the score of correct answers in the relative directions task

4.3.2 DISTANCE ESTIMATION

DESCRIPTIVE ANALYSIS

Distance estimation results, Table 9, show similar central tendency between groups, but greater variability in the Control group. Both the Control and Experimental groups have the same mode and median (50th percentile), and range of values from 0 to 2, However, the Control group displays a wider spread of scores, with the 75th percentile at 2 compared.

Table 9 Descriptive analysis of the total correct responses from both the Control and Experimental groups in the Distance Estimation task

	Distance_Estimation	
	Control	Experimental
Mode	1	1
Minimum	0	0
Maximum	2	2
25th percentile	0	0
50th percentile	1	1
75th percentile	2	1

The histogram, Figure 4-9, illustrates that the Control group achieved scores distributed across 0, 1, and 2, with a higher frequency at 1. While the Experimental group exhibited a concentration of scores primarily at 1, followed by 0, with fewer participants achieving a score of 2, showing a lower value of high scores compared to the Control group.

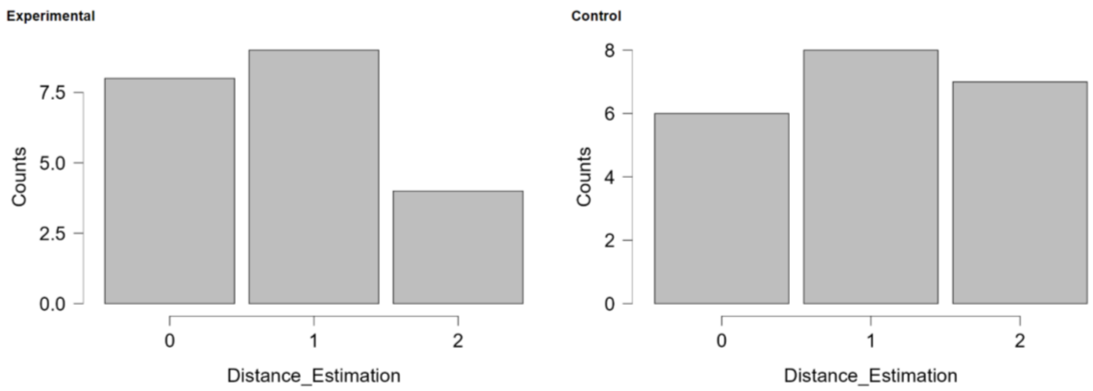

Figure 4-9 Data distribution of the summation of the correct answers for both groups for Distance Estimation task

STATISTICAL ANALYSIS

Table 10 presents the Bayes factor BF_{+0} = 0.201, as determined by the Bayesian Mann-Whitney test.

Table 10 Results of Bayesian mann-whitney test of the Distance Estimation task

	BF_{+0}	W	Rhat
Distance_Estimation	0.201	184.0	1.000

Figure 4-10 shows the prior and posterior probability distribution with the 95% credible interval [0.006, 0.537] which is slightly above zero, with a posterior median effect size of 0.137. The Bayes factors are BF_{+0} = 0.201 and BF_{0+} = 4.966. The relative likelihood depicted in the pizza graph illustrates the data under (H_+) and (H_0), with the probability distribution under (H_0) being notably dominant.

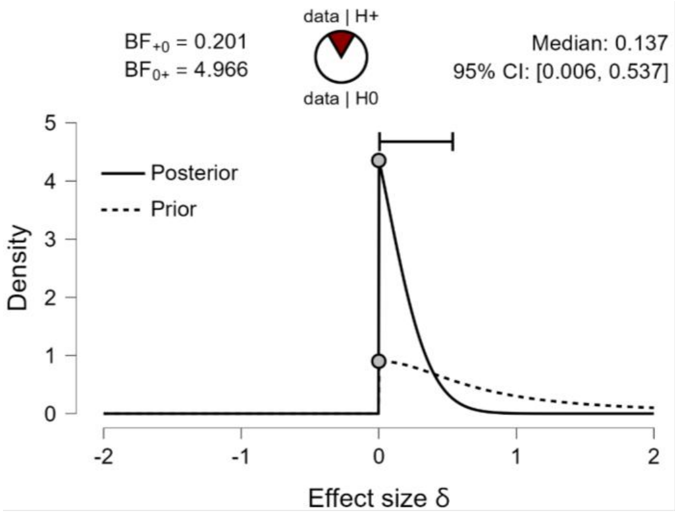

Figure 4-10 Prior and posterior probability distribution of the score of correct answers in the distance estimation task

4.3.3 CAMERA ORIENTATION

DESCRIPTIVE ANALYSIS

Table 11, Camera orientation scores are almost identical across groups, with both the Control and Experimental groups showing a mode and median of 0 and scores ranging from 0 to 2. The 25th percentile is 0 and the 75th percentile is 1 in both groups.

Table 11 Descriptive analysis of the total correct responses from both the Control and Experimental groups in the Camera orientation task

	Camera_Orientation	
	Experimental	Control
Mode	0	0
Minimum	0	0
Maximum	2	2
25th percentile	0	0
50th percentile	0	0
75th percentile	1	1

Figure 4-11, The histograms indicate a strong floor effect for camera orientation in both groups, most of the participants got scoring 0 and only few observations at higher scores of 1 and 2; the two group distributions look similar, suggesting minimal group differences.

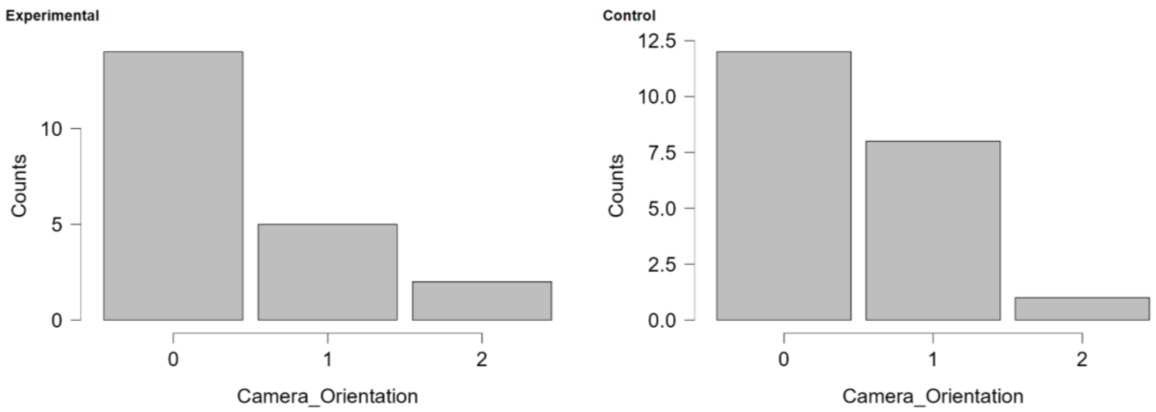

Figure 4-11 Data distribution of the summation of the correct answers for both groups for the Camera orientation task

STATISTICAL ANALYSIS

Table 12 Results of Bayesian mann-whitney test of the Camera orientation task

	BF_{+0}	W	Rhat
Camera_Orientation	0.293	205.0	1.000

Table 12 illustrates the result of the Bayesian Mann-Whitney U test which shows a Bayes factor value (BF_{+0} = 0.293). The prior and posterior distribution graph, Figure 4-12, shows a small positive effect, with a posterior median effect size of 0.179. The 95% credible interval [0.008,0.654] and a pizza plot with higher probability under (H_0).

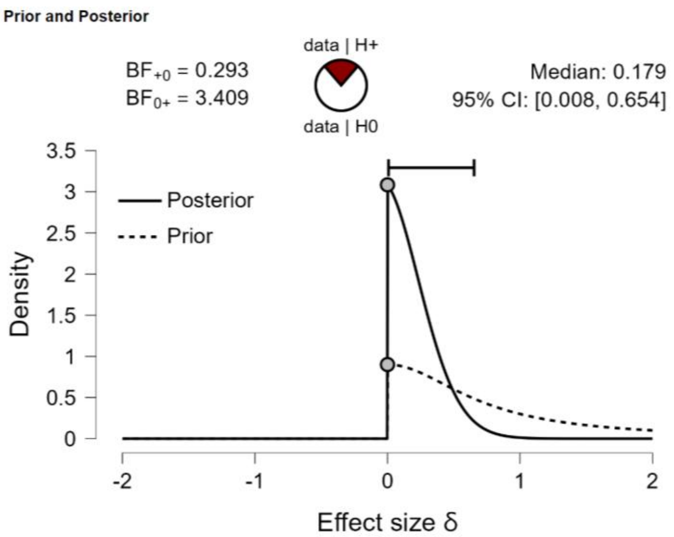

Figure 4-12 prior and posterior probability distribution of the score of correct answers in Camera Orientation task

4.3.4 LAYOUT IDENTIFICATION

DESCRIPTIVE ANALYSIS

Table 13 presents a summary of the responses of the layout identification task. In both groups, the scores range from 0 to 3, indicating variability. In the Control group, the most frequently observed score is 2, with the 75th percentile also at 2, suggesting that few participants achieved a score of 3. Conversely, in the Experimental group, the mode is 1, and the median (50th percentile) is 2, with the 75th percentile at 2, indicating that scores of 1 and 2 are the most attained.

Table 13 Descriptive analysis of the total correct responses from both the control and experimental groups in the layout identification task

	Layout_Identification	
	Experimental	Control
Mode	1	2
Minimum	0	0
Maximum	3	3
25th percentile	1	1
50th percentile	2	1
75th percentile	2	2

Figure 4-13 reveals a generally similar distribution, with clusters at the values of 1 and 2. There is a shift toward higher scores in the Experimental group, by having two values of mode of 1 and 2, and a slightly elevated frequency at the maximum score of 3.

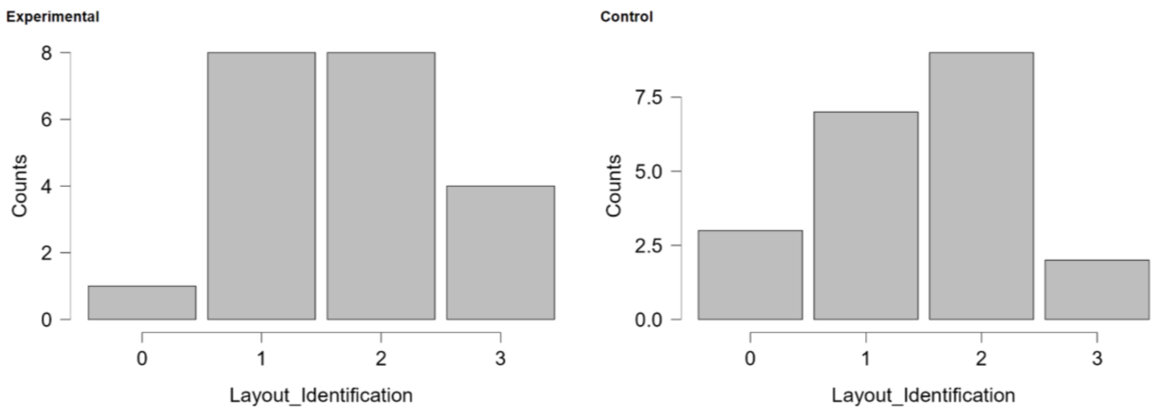

Figure 4-13 Data distribution of the summation of the correct answers for both groups for the layout identification task

STATISTICAL ANALYSIS

Table 14 Results of Bayesian mann-whitney test of the Layout Identification task

	BF_{+0}	W	Rhat
Layout_Identification	0.620	249.5	1.000

For Layout Identification, Table 14, the Bayesian analysis shows The Bayes factor BF_{+0} = 0.620. While the graph, Figure 4-14, shows that a 95% probability that the true value of δ lies within the range [0.017, 0.833], with the value of 0.300 as a center of the posterior probability mass. The Bayes factors is BF_{+0} <1 with a value of 0.62. additionally, the pizza plot displays probability distribution of the data under (H_0) being slightly more dominant.

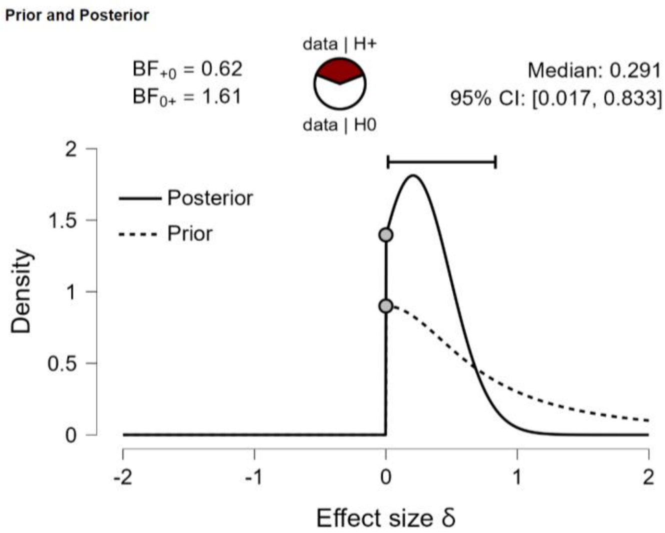

Figure 4-14 Prior and posterior probability distribution of the score of correct answers in the Layout Identification task

4.3.5 CAMERA LOCATION AWARENESS

DESCRIPTIVE ANALYSIS

Table 15 show that camera location awareness scores are comparable across groups, with identical percentiles values of 1 (25th percentile) and 2 (50th and 75th percentiles) and central tendency with mode of 2.

Table 15 Descriptive analysis of the total correct responses from both the Control and Experimental groups in the camera location awareness task

	Camera_Location_Awareness	
	Experimental	Control
Mode	2	2

	Camera_Location_Awareness	
	Experimental	Control
Minimum	0	1
Maximum	3	3
25th percentile	1	1
50th percentile	2	2
75th percentile	2	2

Figure 4-15 shows that in both groups, camera location awareness scores cluster at 2, with most values falling between 1 and 3, however, few participants in the Experimental group achieved 0 scores and slightly fewer frequency of high values.

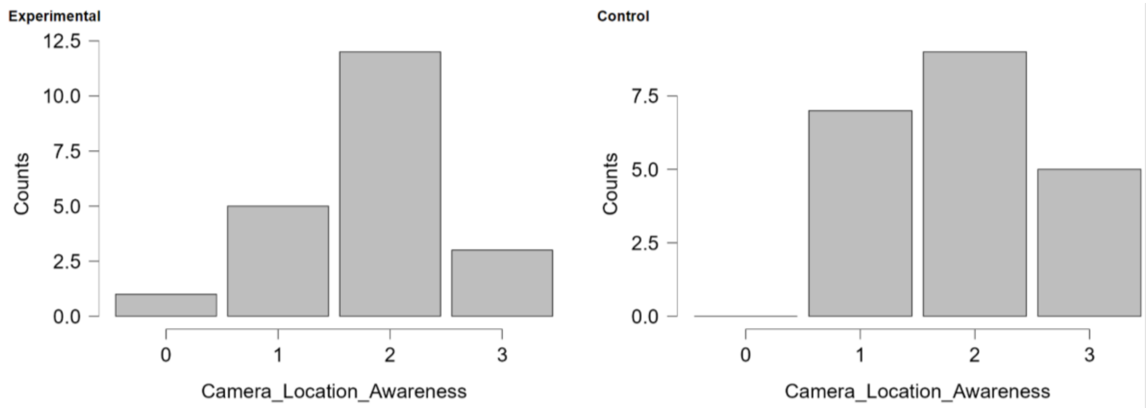

Figure 4-15 Data distribution of the summation of the correct answers for both groups for the camera location awareness task

STATISTICAL ANALYSIS

Table 16 Results of Bayesian mann-whitney test of the Camera Location Awareness task

	BF_{+0}	W	Rhat
Camera_Location_Awareness	0.253	211.0	1.000

The Bayesian analysis, as presented in Table 16, indicates a Bayes factor (BF_{+0}) of 0.253, which is less than 1. Furthermore, Figure 4-16 illustrates a small positive effect, with a posterior median effect size of 0.162 and a 95% credible interval [0.007,0.599]. Additionally, the pizza scale demonstrates a higher probability under (H_0).

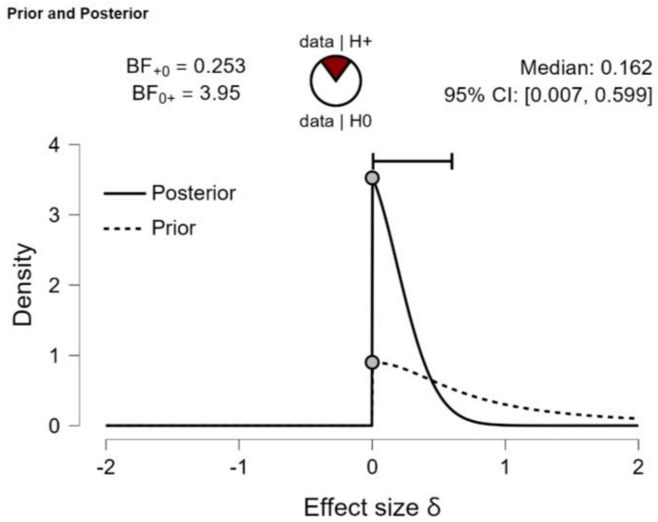

Figure 4-16 Prior and posterior probability distribution of the score of correct answers in the Camera Location Awareness task

4.4 RESULTS OVERVIEW

Given that the study comprises eight tasks, this section summarizes the key results across all tasks to provide a more concise comparative overview.

Landmark Identification: descriptive analysis indicates that participants in the Experimental group tend to achieve perfect scores more than those in the Control group with similarity in the range of high scores. However, the Bayesian test supports (H_0), indicating no significant difference between the two groups. This conclusion is also supported by prior and posterior results, which suggest that the data are approximately 1.583 times more likely under (H_0). Consequently, the Bayes factor and probability graph provide **anecdotal evidence in favor of (H_0),** reporting no difference between the two groups.

Landmark Organization: the summary of the values shows that higher frequent scores with the Experimental group than the values of the Control group with varity of scores in both groups. the Bayesian analysis points to **anecdotal evidence in favor of (H_0)** where BF_{+0} = 0.757.

Route Choice: the descriptive results of the task performance is largely similar across groups, with overlapping distributions. Meanwile the bayesian analysis supports the same conclusion by having the Bayes factors with values of BF_{+0} = 0.312 and BF_{0+} = 3.209 which indicates the data are approximately 3.209 times more likely under (H_0)

and implies anecdotal to **moderate evidence for (H_0)** indicating that the two groups don't have a significant difference.

Relative Direction: the descriptive summaries indicate that the Experimental group exhibits higher relative direction scores compared to the Control group, suggesting superior performance. The Bayesian analysis provides a Bayes factor of BF_{+0} = 2.666, which indicates **anecdotal (approaching moderate) evidence supporting (H_+), and this indicates that the experimental group outperforms the control group** and that conclusion is also supported by the visualization of pizza. Furthermore, the Bayes factor suggests that the data are approximately 2.666 times more likely under the alternative hypothesis, and this conclusion is also supported by the visualization of the pizza graph by displaying that the probability of data ubder (H_+) is more prominent.

Distance Estimation: the summary statistics reveal that the distance estimation performance is comparable between groups due to the similarity in their statistics and distribution; however, the Control group shows larger proportions of higher scores. The statistical analysis results indicate a Bayes Factor (BF_{+0}) of 0.201, suggesting **moderate evidence in support of (H_0).** Additionally, the Bayes Factor (BF_{0+}) of 4.966 reflects the probability of the data being more likely under (H_0) as well. The relative likelihood, as depicted in the pizza graph, illustrates that the probability distribution under H_0 being notably predominant. The conclusion drawn from this analysis reveals that there is no significant difference between the two groups in the distance estimation task.

Camera Orientation: The analysis of results reveals no significant differences between the groups because of their nearly identical scores and similar distribution patterns. Furthermore, a majority of participants in both groups shoed a tendency to achieve a score of zero, indicating a floor effect. This suggests that most participants in both groups were unable to attain high scores in this task. However the bayesian anaysis revealed BF_{+0} = 0.293 which indicate **moderate evidence in support of (H_0)**, revealing no difference between both groups.

Layout Identification: The descriptive analysis revealed minimal differences with the same data variation, and the data were predominantly clustered around the median scores in both groups. However, the experimental group exhibited a tendency to achieve higher scores. Furthermore, the Bayes factor BF_{+0} = 0.620 indicates **anecdotal evidence in support of the null hypothesis (H_0), which** means that there is no significant difference between the two groups in the layout identification task.

Camera location awareness: The control group possesses higher scores comparing to the experimental group, however they have the same range of values. The Bayes factor BF_{+0} = 0.253, less than 1, indicates that the data are more likely under (H_0). BF_{0+} means the data are approximately 3.95 times more likely under (H_0), by these values of bayes fator they give **moderate evidence in favour of (H_0),** indicating no difference between the two groups in performing the camera location awareness task.

5. DISCUSSION

5.1 RESULTS DISCUSSION

The study aims to explore the effect of pre-existing survey knowledge concerning neighboring areas on the spatial knowledge acquired passively in cooperation with VGLs being embedded in a navigational video. Previous research has primarily examined the influence of prior survey knowledge on familiar navigational areas. In this study, the navigational area is unfamiliar to all participants, while only the experimental group possesses survey knowledge of the broader environment.

This section is to discuss the outcomes of the tasks included in this study and interpret them to evaluate the hypotheses by considering the findings related to each type of spatial knowledge, then addressing the research question. The hypotheses are interpreted as follows:

H1: *Navigators with prior survey knowledge about the broader environment will show better performance in recalling landmarks, the sequence of landmarks and routes taken along a route.*

The findings from landmark identification, landmark organization, and route choice tasks indicate that the acquisition of landmark and route knowledge for an unfamiliar route is independent of prior survey knowledge of the surroundings. This conclusion is drawn from the similarity in results observed between the two groups, regardless of their survey knowledge of the broader areas. The similarity of results suggests that the recognition of features, the ability to recall their sequence, and the actions taken at those features (i.e., route choices) is because both groups received identical information through a video with integrated VGLs which facilitate spatial learning for the two groups.

In the task of landmark identification, both groups demonstrated high scores, indicating that passive spatial learning from a video with embedded VGLs significantly influences the encoding of landmarks. This finding aligns with(Qiu et al., 2020), who suggested that passive learning facilitates the memorization process due to the absence of distractions, in contrast to active learning.

H2: *Navigators with survey knowledge about the broader environment will be able to provide more correct answers in survey knowledge tasks.*

- ***H2a*: *Navigators with survey knowledge about surrounding environment would build more precise mental representation of the route.***

The mental representation of the route was assessed using a layout identification task. The results did not confirm the sub-hypothesis and did not indicate a difference in understanding the layout of an unfamiliar route due to the presence of survey knowledge about the areas surrounding the navigated route. The results point to a contrast with the literature which clarified that survey knowledge within the navigational environment facilitates understanding of the layout of an environment (Demirbaş, 2001). This contrast may highlight the finding by Afrooz et al.(2018) that active learning contributes more to the development of mental maps and environmental configurations than passive learning.

- ***H2b:*** *Navigators with survey knowledge about surrounding environment will be aware of the camera location and orientation along the path.*

The findings do not corroborate the sub-hypothesis, as they fail to demonstrate significant differences based on prior survey knowledge. Literature indicates that survey knowledge enhances self-localization, and by using global landmarks navigators maintain a consistent bearing along a route. Additionally, other studies suggest that VGLs facilitate the spatial updating of orientation and position during the navigation of a novel route(Liu, Singh, Wunderlich, et al., 2022; Steck & Mallot, 2000), which contrasts with the outcomes of this study. This contrary suggests that passive learning through a first-person video did not enable participants to comprehend the route of the navigation or to update the locations and directions of the camera, despite having knowledge of the surroundings and the broader spatial context obtained from viewing the VGLs.

- ***H2c:*** *Navigators with survey knowledge about surrounding environment will be able to provide more precise relative directions and distance estimation.*

The existing literature, (Chen & Li, 2020; Chrastil & Warren, 2015; He et al., 2019; Wen et al., 2011), supports that possessing survey knowledge facilitates understanding of spatial relationships between locations along a route, including distances and directions. However, the findings offer partial support for the sub-hypothesis. In tasks involving distance estimation, the results did not indicate any significant differences.

Conversely, the data reveals an advantage in tasks involving relative directions when navigators have prior survey knowledge of the surrounding areas, consistent with previous studies. This indicates that existing survey knowledge of the environment surrounding the area of navigation affects the understanding of directional relationships between landmarks on novel routes. In contrast, the results of distance estimation tasks do not align with previous literature, suggesting that comprehension of the broader environmental context does not necessarily influence distance estimation along an unfamiliar route.

Based on the interpretation of the results pertaining to each category of spatial knowledge, it is now possible to address the research question:

RQ: *What is the influence of prior survey knowledge about the broader environment on the acquired knowledge in a simulated path-following wayfinding task with embedded VGLs through a first-person video?*

The findings indicate that prior knowledge of the surrounding environment does not impact the encoding process of route components, such as landmarks and route segments. However, it appears to influence the comprehension of directional relationships between landmarks along a route in a novel environment. This observation supports the refinement by (Schwering et al., 2017) of the wayfinding taxonomy proposed by (Wiener et al., 2009) concerning the path-following task, suggesting that this task should be categorized when prior survey knowledge of the surroundings is present.

5.2 LIMITATIONS

The study is constrained by the specific conditions of the city, neighborhood, participant characteristics, and the questions posed. Additionally, this thesis uses a video-based paradigm that only partially simulates real-world passive navigation, as participants observe the environment and are limited to the camera’s viewing angle.

Integrating the VGLs into a video of real-world settings presented significant challenges, as it required pausing to reveal the underlying view. In the AR system, the display of VGLs was continuous, obvious upon the participants' orientation towards the VGLs.

Although Bayesian analysis is well-suited for small sample sizes, the small sample size of 21 participants per group is still considered a limitation as it reduces the statistical power by amplifying the impact of individual differences over that of group differences, hence it limits the ability to detect smaller effects.

In the experiment, a few participants exhibited unexpected behavior by selecting the 'not sure' option, as it was quicker. However, in this study, this choice had a negligible impact on the results due to the limited number of participants selecting this option (Appendix A).

The investigation into camera orientation revealed a floor effect and this effect raises the question of whether the difficulty arose from the methodology of analysis used or from the nature of the questions themselves.

5.3 THEORETICAL AND PRACTICAL IMPLICATIONS

This study investigates the role of prior survey knowledge of the broader environment in a first-person video simulated wayfinding task with integrated virtual global landmarks. The findings might suggest that having prior survey knowledge facilitates understanding of the relative directions between landmarks along a route.

These results might suggest theoretical implications for spatial cognition research and might support the argument raised by Schwering et al., (2017) by providing a clearer conceptualization of the path-following task within the wayfinding taxonomy proposed by Wiener et al.(2009).

There may be methodological implications as well. The integration of virtual global landmarks in first-person video paradigms might suggest a novel approach for manipulating survey knowledge in experiments, and there may be an implication for further research to understand the spatial knowledge acquired during path-following when using this paradigm. Furthermore, the development of a reproducible prototype using open data (Appendix A) may have methodological implications for future research by enabling replication and extension of this methodological approach.

5.4 DIRECTIONS FOR FUTURE RESEARCH

While the present study provides meaningful insights into the passive acquisition of spatial knowledge from videos with embedded VGLs, it also highlights potential directions for future research. This includes extending the study to active learning with VGLs, as seen in the initial AR system, given the ongoing debate about the effectiveness of passive learning from videos and the contrast between the results and literature.

The study's findings emphasize the need for further investigation into the body-orientation, camera orientation with navigation video, task in future research due to the floor effect observed, which suggests that it could be explored through active learning or examined in recorded videos within a virtual environment that allows for a continuous view of the VGLs during navigation.

While in the present study was conducted remotely, it was challenging to maintain standardization across all participants with a sketch-map task, another recommendation arises which is to reduce number of tasks through employment of a sketch-map task as through it we can analyze the understanding of distances, angles and understanding the overall layout.

Enhancing the sensitivity of tasks measures can be achieved by increasing the number of questions per task and expanding the sample size, as these adjustments will enhance statistical power. Finally, the last recommendation is having questions with clear right or wrong answers, rather than options like 'not sure,' to simplify the analysis. This method also improves control over participants' motivation by encouraging them to make a decision and choose the answer they believe is most correct.

6. CONCLUSION

This research aimed to assess whether the path-following task within the wayfinding taxonomy (Wiener et al., 2009) should be categorized, considering the argument by Schwering et al. (2017) by implementing a novel approach to Virtual Global Landmarks (VGLs) through their integration into a navigational video. The study hypothesized that navigators possessing prior survey knowledge of the surrounding environments exhibit superior spatial knowledge acquisition compared to those lacking such knowledge. An online experiment was conducted to assess tasks related to each type of spatial knowledge: landmarks, route, and survey knowledge.

Bayesian statistical analysis was conducted on data resulting from landmarks, route, and survey knowledge tasks. Notably, in the relative direction task, the results revealed anecdotal evidence, bordering on moderate, of the superiority of the group familiar with the broader spatial context of the study. The interpretation of the results suggests that possessing survey knowledge of nearby environments does not affect tasks related to memorizing landmarks or route segment. However, among the survey knowledge tasks, it indicates a better understanding of the directional relationships between landmarks.

Despite the contributions of this study, it has certain limitations. The video simulates passive navigation that is limited to the camera's angle. The proposed system does not offer continuous viewing of the VGLs. Additionally, the sample size is small, and there are anecdotal 'not sure' responses to a few questions. The camera-orientation task reveals a floor effect. Therefore, it is recommended that future studies incorporate active learning methodologies, increase the number of questions with a larger sample size, and include only right or wrong answers to avoid unexpected behavior. Furthermore, a different analysis technique could be used for camera orientation, with easier questions.

In conclusion, this thesis demonstrates that possessing survey knowledge of broader areas can influence the comprehension of relationships between features on an unfamiliar route. The study provides a theoretical outcome by challenging the simplified view of path-following wayfinding task, suggesting that it involves more than encoding features and their sequence; it can include establishing directional relationships between these features, and this is aligned with the refinement that the path-following wayfinding task should be categorized. This contributes to a better understanding of the wayfinding taxonomy and the spatial knowledge associated with each task, which can aid in urban design and the development of navigational systems. Additionally, it offers an initial methodological framework that can be utilized in future research.

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APPENDIX A

A- Verification of Levenshtein Distance Calculations:

Levenshtein distance calculations were verified using available online computational tools. These platforms were used to cross-check programmatically generated results, ensuring the correctness of the calculated distances in the data sheet.

- https://planetcalc.com/1721/
- https://awsm-tools.com/levenshtein-distance
- https://rapidtoolset.com/en/tool/levenshtein-distance-calculator

B- Arrangement score of Levenshtein Distance:

To standardize the Levenshtein distance values to a scale with ordinal values from 0 to 10 where 10 represents the perfect score of arrangement, the following normalization formula was applied:

$$\text{Normalized Score} = 10 - Levenshtein\_distance$$

Where:

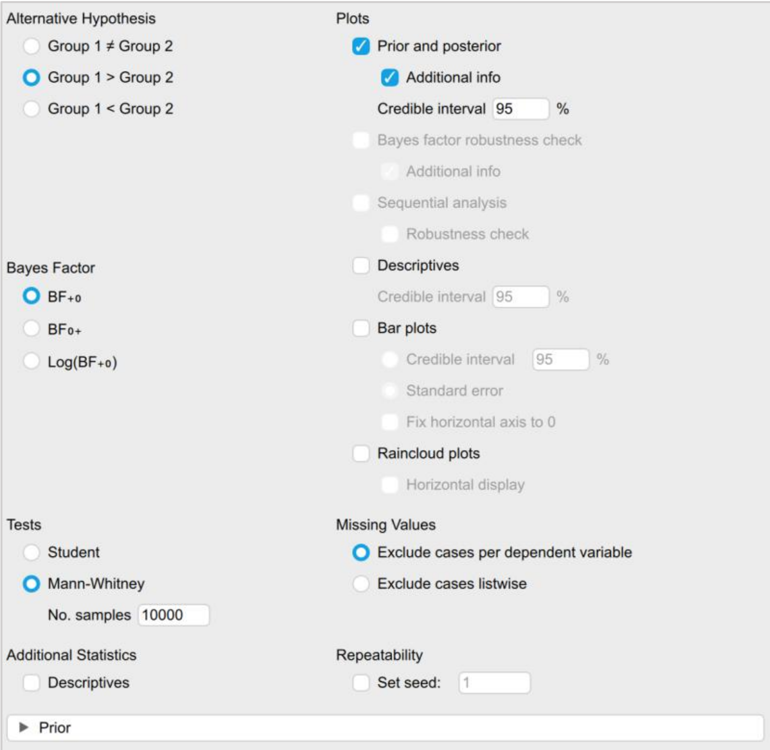
- $Levenshtein\_distance$ represents the value of the calculated Levenshtein distance, A Levenshtein distance of a value of 0 indicates a perfect match (i.e., complete accuracy), whereas increasing values reflect progressively lower sequence accuracy.
- 10 corresponds to the number of characters involved in the arrangement task.

C- The navigational video used in the experiment is publicly available on YouTube and can be accessed via the following link:

https://www.youtube.com/watch?v=45tlHkvoBoc

D- A screenshot displaying the selected options and parameter settings used in the Bayesian analysis to document the analytical configuration applied during model estimation, ensuring transparency and reproducibility of the statistical procedures.

The displayed settings correspond to the final model specifications reported in the Results section.



Notes:

- For all tests, the alternative hypothesis specifies that the location of group Experimental is greater than the location of group Control.
- Result based on data augmentation algorithm with 5 chains of 10000 iterations.

E- Scribbr was used to support the understanding of specific experimental design concepts during the preparation of this study. The resource was used for conceptual guidance and did not contribute to data collection, analysis, or the formulation of results: https://www.scribbr.com/

F- All supplementary materials related to this study are publicly available via Zenodo. The repository includes:

- The survey output dataset (raw data export, Levenshtein distances and arrangement score, ready-to-use data for analysis).
- Materials used for the development of experimental videos.
- The complete set of survey questions includes the correct answers.
- The raw navigational video.
- The final video was used in the experiment.
- Video recordings for all participant conditions, illustrating differences between:
    - The control group (the video recording conducting the whole survey)

- The experimental group (to show the different questions regarding the navigation area knowledge)
- The excluded group (participants with prior knowledge of the study area).

The Zenodo repository can be accessed via the following link:

https://zenodo.org/records/18423437

G- The ArcGIS Pro project file is included in the Zenodo repository and contains all maps and feature classes used to generate the cartographic materials presented in the Methodology chapter.

The project structure allows for reproducibility and future extension, enabling additional maps or experimental questions to be developed using the same spatial datasets and configuration. This ensures transparency and facilitates the reuse of materials in subsequent research.

https://zenodo.org/records/18423979

APPENDIX B

Ethics committee approval email

From Ethics Committee <ethicscommittee@novaims.unl.pt>
Date Tue 11/18/2025 7:02 AM
To hala.ghareeb117@gmail.com <hala.ghareeb117@gmail.com>; Hala Abdelmaksoud Hamed Ghareeb <20240762@novaims.unl.pt>; Marco Painho <painho@novaims.unl.pt>
Cc Ethics Committee <ethicscommittee@novaims.unl.pt>

Dear Hala Ghareeb,
Dear Professor Marco Painho,

Thank you for filling out the Research Ethics Checklist. After reviewing your request, you can proceed with the study, as we do not foresee any major ethical concerns with the project.

Project No.: **GEO2025-10-301662**

Project Title: **Testing the new Taxonomy of Human Wayfinding Tasks: Testing the influence of survey knowledge about surrounding environment on path following tasks**

Principal Researcher: **Hala Ghareeb**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 18/11/2025.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 18/11/2025
NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

This email serves as formal proof of ethical approval. If required for inclusion in a thesis, dissertation, or any other academic documentation, a PDF version of this message may be created and attached accordingly.

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