Human Spatial Navigation in the Digital Era

Effects of Landmark Depiction on Mobile Maps on Navigators' Spatial Learning and Brain Activity during Assisted Navigation

---

Dissertation

zur

Erlangung der naturwissenschaftlichen Doktorwürde

(Dr. sc. nat.)

vorgelegt der

Mathematisch-naturwissenschaftlichen Fakultät

der

Universität Zürich

von

Bingjie Cheng

aus

China

Promotionskommission:

Prof. Dr. Sara Irina Fabrikant (Vorsitz und Leitung)

Prof. Dr. Klaus Gramann (Leitung)

Prof. Dr. Robert Weibel

Zürich, 2023

Abstract

Navigation was an essential survival skill for our ancestors and is still a fundamental activity in our everyday lives. To stay oriented and assist navigation, our ancestors had a long history of developing and employing physical maps that communicated an enormous amount of spatial and visual information about their surroundings. Today, in the digital era, we are increasingly turning to mobile navigation devices to ease daily navigation tasks, surrendering our spatial and navigational skills to the hand-held device. On the flip side, the conveniences of such devices lead us to pay less attention to our surroundings, make fewer spatial decisions, and remember less about the surroundings we have traversed. As navigational skills and spatial memory are related to adult neurogenesis, healthy aging, education, and survival, scientists and researchers from multidisciplinary fields have made calls to develop *a new account of mobile navigation assistance* to preserve human navigational abilities and spatial memory.

Landmarks have been advocated for special attention in developing cognitively supportive navigation systems, as landmarks are widely accepted as key features to support spatial navigation and spatial learning of an environment. Turn-by-turn direction instructions without reference to surrounding landmarks, such as those provided by most existing navigation systems, can be one of the reasons for navigators' spatial memory deterioration during assisted navigation. Despite the benefit of landmarks in navigation and spatial learning, long-standing literature on cognitive psychology has pointed out that individuals have only a limited cognitive capacity to process presented information for a task. When the learning items exceed learners' capacity, the performance may reach a plateau or even drop. This leads to an unexamined yet important research question on how to visualize landmarks on a mobile map to optimize navigators' cognitive resource exertion and thus optimize their spatial learning.

To investigate this question, I leveraged neuropsychological and hypothesis-driven approaches and investigated whether and how different numbers of landmarks depicted on a mobile map affected navigators' spatial learning, cognitive load, and visuospatial encoding. Specifically, I set out a navigation experiment in three virtual urban environments, in which participants were asked to follow a given route to a specific destination with the aid of a mobile map. Three different numbers of landmarks—3, 5, and 7—along the given route were selected based on cognitive capacity literature and presented to 48 participants during map-assisted navigation. Their brain activity was recorded both during the phase of map consultation and during that of active locomotion. After navigation in each virtual city, their spatial knowledge of the traversed routes was assessed.

The statistical results revealed that spatial learning improved when a medium number of landmarks (i.e., five) was depicted on a mobile map compared to the lowest evaluated number (i.e., three) of landmarks, and there was no further improvement when the highest number (i.e., seven) of landmarks were provided on the mobile map. The neural correlates that were interpreted to reflect cognitive load during map consultation increased when participants were processing seven landmarks depicted on a mobile map compared to the other two landmark conditions; by contrast, the neural correlates that indicated visuospatial encoding increased with a higher number of presented landmarks. In line with the cognitive load changes during map consultation, cognitive load during active locomotion also increased when participants were in the seven-landmark condition, compared to the other two landmark conditions.

This thesis provides an exemplary paradigm to investigate navigators' behavior and cognitive processing during map-assisted navigation and to utilize neuropsychological approaches to solve cartographic design problems. The findings contribute to a better understanding of the effects of landmark depiction (3, 5, and 7 landmarks) on navigators' spatial learning outcomes and their cognitive processing (cognitive load and visuospatial encoding) during map-assisted navigation. Of these insights, I conclude with two main takeaways for audiences including navigation researchers and navigation system designers. First, the thesis suggests *a boundary effect* of the proposed benefits of landmarks in spatial learning: providing landmarks on maps benefits users' spatial learning only to a certain extent when the number of landmarks does not increase cognitive load. Medium number (i.e., 5) of landmarks seems to be the best option in the current experiment, as five landmarks facilitate spatial learning without taxing additional cognitive resources. The second takeaway is that the increased cognitive load during map use might also *spill over* into the locomotion phase through the environment; thus, the locomotion phase in the environment should also be carefully considered while designing a mobile map to support navigation and environmental learning.

Publications

Journal Articles

B Cheng, A Wunderlich, K Gramann, E Lin, SI Fabrikant (2022). The effect of landmark visualization in mobile maps on brain activity during navigation: A virtual reality study. *Frontiers in Virtual Reality*, 3, 981625. DOI: https://doi.org/10.3389/frvir.2022.981625

> Author Contributions: BC, KG, and SF designed the study. BC performed data collection. BC performed data analysis. AW, KG, and EL assisted with data analysis. BC drafted the manuscript and all authors were involved in revising the manuscript. The authors read and approved the final manuscript.

B Cheng, E Lin, A Wunderlich, K Gramann, SI Fabrikant (2023). Using eye blink-related brain activity to investigate cognitive load during assisted navigation. *Frontiers in Neuroscience*, 17, 1024583. DOI: https://doi.org/10.3389/fnins.2023.1024583

> Author Contributions: BC, KG, and SF designed the study. BC performed data collection and drafted the manuscript. BC and EL performed data analysis. AW and KG assisted with data analysis. All authors were involved in revising the manuscript and read and approved the final manuscript.

Conference Contributions

B Cheng, E Lin, A Wunderlich, K Gramann (2022). Eye blink-related brain potentials during landmark-based navigation in virtual reality (short paper, presentation).15th International Conference on Spatial Information Theory (COSIT), Kobe Japan, September 5-9 2022.

B Cheng, E Lin, A Wunderlich, K Gramann, SI Fabrikant (2022). Using eye blinks as event markers to investigate cognitive load during navigation (abstract, poster). Neuroergonomics Conference (NEC). New York, USA, July 29-31 2022

B Cheng, T Reichenbacher (2022). Adapting geographic relevance on mobile maps with a neuroadaptive approach. UZH DSI Mobility Workshop (abstract, poster). Maienfeld, Switzerland, June 30 - July 1 2022

B Cheng, A Wunderlich, K Gramann, SI Fabrikant (2021). The effects of the number of landmarks in mobile maps on cognitive load during navigation (abstract, poster). Neuroergonomics Conference (NEC). Munich, Germany, September 11-16 2021

B Cheng, I Ruginski, SI Fabrikant (2021). The effects of landmark visualization in mobile maps on spatial learning during navigation (abstract, poster). Spatial Cognition. Riga, Latvia, August 1-4 2021

B Cheng (2019). Enhancing spatial learning during navigation using a neuroadaptive approach (doctoral colloquium). 14th International Conference on Spatial Information Theory (COSIT), Regensburg, Germany, September 9-13, 2019

Funding

This work was supported by the H2020 European Research Council (ERC) Advanced Grant GeoViSense (740426). https://cordis.europa.eu/project/id/740426.

The funder had no role in the study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Acknowledgments

Doing a PhD can be a very lonely and frustrating journey, locked away in an office or a laboratory, reading literature, conducting experiments, running analyses, generating figures, and writing papers. However, my PhD journey was one of the most pleasurable experiences in my life, with a lot of joy, fulfillment, and fun. I would like to express my sincere gratitude to everyone who accompanied me along this journey and made the journey wonderful.

First, I am most grateful to Prof Dr Sara Irina Fabrikant for offering me this opportunity to work with her and for being such an encouraging, professional, and inspiring advisor. Thank you for guiding me through this fascinating interdisciplinary research path with your full trust and support. Also thank you for the evenings we rocked with music. More fun continues down the road.

I am also particularly grateful to Prof Dr Klaus Gramann for being a supportive, professional, and engaging co-advisor. Thank you for always providing prompt help and insightful input, especially for experimental design, EEG analysis, and paper writing. Also thank you very much for hosting me in Berlin, and for the awesome hotpot and farewell cocktail night.

A very special thank you is directed to Prof Dr Robert Weibel for being such a supportive and pleasant committee member. I always appreciate your valuable feedback and insights for my PhD thesis and my academic career with your expertise.

I would like to express my gratitude to my amazing collaborators, who have significantly contributed to my PhD thesis. Thank you, Dr Tyler Thrash, Dr Ian Ruginski, Armand Kapaj, Dr Enru Lin, Alex Sofios, and Dr Anna Wunderlich. My PhD thesis is an outcome of excellent teamwork and team spirit.

I would also like to thank my lovely colleagues from the University of Zurich, especially those from the GIScience Center and Digital Society Initiative: Karin, Donatella, Corrado, Tumasch, Oliver, Sara Lanini-Maggi, Qi, Sascha, Annina, Max, Daniella, Manuel, Ross, Inhye, Hoda, Zhiyong, Cheng, Peter, Nico, Changyu, Alexandra, Simon, Simona, Nina, and many others. Thank you for the stimulating scientific discussions and the fun moments outside of work. The beat still goes on.

I would also like to thank my colleagues from TU Berlin: Chris, Zak, Timo, Marius, Sheng, Lukas, Sein, Bilal, Oliver, and those from Liverpool John Moores University: Steve, Felix, Kelly-Ann, Chris, and David. Thank you for providing great company when I was abroad.

Finally, I thank my lovely family in China and my sincere friends outside of my work environment, especially those in Switzerland, China, the US, Germany, France, and the UK, for being such great and continuous company for me for the past years.

"No matter what, nobody can take away the dances we've already had."

—— Gabriel García Márquez

Contents

Abstract ... ii

Publications ... v

Acknowledgments ... vii

Contents ... ix

List of Figures ... xiv

List of Tables ... xvi

Chapter 1: Introduction ... 1

1.1 Motivation and problem statement ... 1

1.2 Research gaps and research questions ... 2

1.3 Thesis approach ... 5

1.4 Relevance ... 6

Chapter 2: Related Work ... 9

2.1 Navigation and spatial learning ... 9

2.1.1 Navigation ... 8

2.1.2 Spatial knowledge acquisition during navigation ... 11

2.2 Navigation assistance ... 13

2.2.1 GPS use and spatial learning ... 16

2.2.2 Cartographic design of mobile map displays ... 17

2.3 Landmarks ... 18

2.3.1 Functions of landmarks 19

2.3.2 Landmark visualization on mobile maps 19

2.4 Cognitive capacity 20

2.4.1 Visuospatial capacity for real-world objects...20

2.4.1 Visuospatial memory in spatial navigation 21

2.4.3 Cognitive load 22

2.4.4 Cognitive load measurement...22

2.5 Electroencephalography (EEG) 23

2.5.1 Event-related potentials (ERPs) 24

2.5.2 Frequency-domain analysis..26

2.5.3 Visual and spatial encoding measured by EEG.......................................27

2.5.4 Cognitive load measured by EEG 28

2.5.5 Examining brain activity during locomotion 30

2.6 Virtual reality as a tool to investigate naturalistic navigation 33

2.7 Summary...34

Chapter 3: Experiment..36

3.1 Independent and dependent variables..36

3.2 Hypotheses 37

3.3 Experimental design 39

3.3.1 Landmark presentation on a mobile map 39

3.3.2 Mobile map display during navigation 42

3.4 Stimuli and apparatus...44

3.4.1 Virtual cities...44

3.4.2 Virtual reality lab 44

3.5. Measurements.. 47

3.5.1 Spatial learning tests 48

3.5.2 EEG data collection 49

3.5.3 Spatial abilities—control variables 50

3.6 Power analysis and participants 51

3.7 Procedure 51

Chapter 4: Analyses 53

4.1 Spatial learning performance 53

4.1.1 Landmark recognition 53

4.1.2 Route direction memory 54

4.1.3 JRD errors 55

4.2 EEG data preprocessing 56

4.3 Brain activity during map consultation 57

4.3.1 Map-event extraction 58

4.3.2 Regions of interest 59

4.3.3 ERP analysis 60

4.3.4 Power spectral analysis 60

4.4 Blink-related brain activity during locomotion 62

4.4.1 Eye blink detection.. 62

4.4.2 Source-based EEG data cleaning 62

4.4.3 Blink-related ERP extraction and analysis 63

4.4.4 Blink-related power spectral analysis–exploratory analysis 64

4.5 Spatial ability analysis 65
4.6 Statistical analysis: linear mixed-effect models 65
Chapter 5: Results 68
5.1 Effects of the number of landmarks on spatial learning 68
5.2.1 Landmark recognition 68
5.2.2 Route direction memory 69
5.2.3 JRD response errors 69
5.2.4 Summary of spatial learning performance 69
5.3 Effects of the number of landmarks on brain activity during map consultation 71
5.3.1 Cognitive load–P3 71
5.3.2 Cognitive load–theta and alpha 72
5.3.3 Early visual encoding–P1 73
5.3.4 Visuospatial encoding–theta and alpha 74
5.3.5 Summary of brain activity during map consultation 75
5.4 Effects of the number of landmarks on brain activity during locomotion 77
5.4.1 Number of blinks during locomotion 77
5.4.2 Blink-related ERP characteristics 77
5.4.3 Cognitive load–blink-related N2 and P3 78
5.4.4 Early visual encoding–blink-related N1 78
5.4.5 Summary of blink-related brain activity 79
Chapter 6: Discussion 81
6.1 Effects of the number of landmarks on spatial learning 81
6.2 Effects of the number of landmarks on brain activity during map consultation 84

6.2.1 Cognitive load—P3 amplitude and theta ERS 84
6.2.2 Visuospatial encoding—theta ERS and alpha ERD 85
6.3 Effect of the number of landmarks on brain activity during locomotion 86
6.3.1 Cognitive load—blink-related P3 and N2 86
6.3.2 Early visual encoding—blink-related N1 87
6.4 Contributions...88
6.5 Future research 90
Chapter 7: Conclusions..93
7.1 Main takeaways 93
7.2 Outlook on human spatial navigation in the digital era 95
References 97
Supplementary Materials...124

List of Figures

Figure 2.1 Proposed taxonomy of navigation tasks, classified by locomotion and wayfinding components.. 9

Figure 2.2 A model of three aspects of spatial knowledge acquisition during navigation....12

Figure 2.3 The 1491 map made by the German cartographer Henricus Martellus..13

Figure 2.4 One map chart of the map collection booklet Mao Kun Map (1621).. 13

Figure 2.5 A) An 64-channel EEG headset measures a participant's brain activity during a task. B) Nomenclature of the 64 EEG electrodes displayed on a head diagram.. 23

Figure 2.6 A) EEG signals with the marked events and the event-locked time windows; B) the ERP waveform averaged across all event windows after the stimulus onset; C) the ERP components in an ERP waveform.. 24

Figure 2.7 Four frequency bands of neural oscillations and their assigned frequency bands.. 26

Figure 2.8 Interaction between the mobile map, the navigator, and the environment during map-assisted navigation. 30

Figure 3.1 The three different landmark conditions along the predefined route in three different virtual environments.. 40

Figure 3.2 The 17 map pop-up spots during navigation and the map presentation from the participants' perspective during navigation...42

Figure 3.3 The sequence of participants' interaction between navigating in the environment and viewing the mobile map... 42

Figure 3.4 Bird's-eye views and the first-person perspectives of the three virtual environments. 44

Figure 3.5 A) The CAVE setup; B) a participant wearing stereoscopic 3D glasses and placing her feet on a foot-operated controller to navigate through the virtual environment... 45

Figure 3.6 Participants titled the controller with their feet to simulate movement in the virtual cities.. 46
Figure 3.7 A participant responding to the spatial learning tests using a 3D responding and pointing device after each navigation trial… 48
Figure 3.8 A flow chart illustrates the procedure of the experiment.. 51
Figure 4.1 An illustration of the JRD error calculation… 54
Figure 4.2 The selected channel clusters to examine cognitive load and visuospatial encoding.. 59
Figure 5.1 Results of spatial learning outcomes… 70
Figure 5.2 The grand averaged amplitudes and the detected peak amplitudes of ERPs for each landmark condition at parieto-occipital leads 71
Figure 5.3 Violin plots of frontal-central relative theta ERS and parieto-occipital relative alpha ERD values of the map-event window indicating cognitive load changes..................72
Figure 5.4 The grand averaged amplitudes and the detected peak amplitudes of the ERP waves for each landmark condition at occipital leads 73
Figure 5.5 Violin plots of parieto-occipital theta ERS, occipital theta ERS, and occipital alpha ERD indicating visual and spatial encoding...74
Figure 5.6 Grand averaged amplitudes of bERPs for three landmark conditions at the fronto-central leads, parieto-occipital leads, and occipital lead.. 79

List of Tables

Table 4.1 Four outcomes of signal detection calculation..53
Table 5.1 Linear regression coefficients of spatial learning performance (i.e., landmark recognition, route direction memory, and JRDs) in the three landmark conditions.............71
Table 5.2 Regression coefficients of peak amplitudes of P3 at parietal-occipital leads and of P1 at occipital leads between the landmark conditions, resulting from the linear mixed-effect models.. 76
Table 5.3 Linear regression coefficients resulting from the linear mixed-effect models of theta ERS and alpha ERD across the three landmark conditions. ERS and ERD were corrected to a pre-experiment baseline.. 76
Table 5.4 Regression coefficients of peak amplitudes of the occipital N1, fronto-central N2, and parieto-occipital P3 across the landmark conditions.. 79

Chapter 1: Introduction

1.1 Motivation and problem statement

"I move, therefore I am" (Murakami, 2011). All living creatures, including humans, move in space. Goal-oriented movement through space is defined as "navigation", which consists of wayfinding and locomotion (Montello, 2005). For our human ancestors, movement and navigation were vital for survival; they moved to hunt, to forage, and to return home safely. Similarly, in modern society, we navigate to work, to shop, to recreate, and more. Therefore, navigation is a fundamental activity and an essential skill in our everyday lives.

When humans navigate, they acquire spatial knowledge about the traversed space. Navigation and spatial knowledge acquisition, especially in novel environments, are cognitively challenging tasks that involve numerous cognitive processes, including perception, memorization, and reasoning about places and orientation(Montello, 2005). These cognitive processes are supported by multiple brain regions (Chrastil, 2013; Do et al., 2021; Ekstrom et al., 2014), and are important not only for navigation but also for healthy brain development, including healthy aging (Coughlan et al., 2018), and spatial reasoning in education (Uttal & Cohen, 2012).

In the digital age, geographic location-based services are available at our fingertips in real time, providing automatic self-localization, route planning, and turn-by-turn directions. With these convenient amenities available in an instance, we whip out our smartphones the moment we start to navigate. In fact, individuals are increasingly using global positioning system (GPS)-enabled mobile devices (Ishikawa, 2019) to find their way and offload the cognitive tasks associated with navigation onto their devices. However, on the flip side of the coin, the frequent use of GPS-based navigation aids leads to "mindless" movement in an environment and has a negative impact on spatial knowledge acquisition of the traversed environment, as has been shown by a large body of literature (Dahmani & Bohbot, 2020; Ishikawa, 2019; Münzer et al., 2012; I. T. Ruginski et al., 2019). Overreliance on GPS-enabled navigation systems may also be detrimental to users' navigational skills (e.g., self-localization and sense of direction (Aporta & Higgs, 2005)), and their spatial transformation skills, such as mental rotation and perspective taking (I. T. Ruginski et al., 2019). Dependence on navigation systems and failure to learn the environments could further negatively affect brain development, such as neurogenesis in the hippocampus—a brain region highly associated with spatial navigation and spatial memory formation (Dahmani & Bohbot, 2020; Toda et al., 2019).

How can we counteract the negative effects of GPS use on users' spatial knowledge acquisition?

This question, serving as the main research motivation, has been the driving force throughout my doctoral research. Hereafter, I present how I tackled this question by applying neuropsychological and cognitive cartographic approaches.

1.2 Research gaps and research questions

It would be helpful for readers to begin this section with a real-world wayfinding scenario[1]. Imagine that you have just arrived in the city where your friend used to live, and you wish to dine at her favorite restaurant. You call your friend and ask for directions from your hotel to the restaurant, which is a few blocks away. Your friend answers the phone and gives you the following directions, such as "turn left at the red building at the corner", "turn right at the Metropolitan Museum with a glass facade", or "go straight and pass the building with

[1] This scenario is based on a real-life experience during my stay in Germany. Some details are modified to make the scenario more general.

the shape of a honeycomb structure". Following her instructions, you successfully arrive at the restaurant. After dinner, you want to visit the night exhibition at the Metropolitan Museum you have passed, but you cannot recall the buildings and the route directions. You probably open a popular commercial mobile map app on your smartphone to search for the route. However, there are hundreds of labels (e.g., businesses, commercial stores, street names) along and off the streets popping on the map. You get frustrated, because you cannot find those buildings at the intersections you have passed over on the map. In the end, you must call your friend again to find the same route back to the museum.

In this scenario, colorful buildings and museums are examples of salient features in an environment known as landmarks. Previous studies have shown that landmarks in an environment help navigators to stay oriented, remember a route, and structure an environment (Evans et al., 1982; Richter & Winter, 2014; Sorrows & Hirtle, 1999). Despite the long-standing literature on the important role of landmarks in human navigation and spatial knowledge acquisition, ubiquitous mobile navigation assistance provided by the big tech industry (e.g., Google, Apple, Meta, and Baidu) typically does not explicitly refer to landmarks–neither visually on the mobile map display nor when providing wayfinding directions. The omission of landmarks in navigation assistance systems may be one reason why navigation systems are often found to negatively affect spatial knowledge acquisition (Anacta et al., 2017; Denis & Fernandez, 2013; Ligonnière et al., 2021; Wenig et al., 2017).

In fact, some researchers have called for the inclusion of landmarks in navigation aids for use cases of pedestrian navigation, citing their ability to help a navigator build a cognitive map and/or to facilitate landmark and route learning (Brügger et al., 2019; Raubal & Winter, 2002; Wunderlich & Gramann, 2021). Despite the proposals of landmark inclusion, few studies have empirically analyzed how landmark depiction on a mobile map influences navigation and spatial learning (Li, 2020; Münzer et al., 2012).

One understudied yet important aspect of map-assisted navigation is the number of landmarks displayed on mobile maps that optimize navigators' spatial learning. As maps are a spatial array containing multiple visual elements that support navigation and spatial learning, they require the activation of cognitive resources, such as visual and spatial working memory, to be utilized effectively. The literature on cognitive capacity suggests that there are limited cognitive resources available for the task at hand (Baddeley, 2003; Sweller, 1988); learning performance reaches a plateau (even drops) when the amount of information to be learned exceeds the learners' limited cognitive capacity.

As described in the aforementioned scenario, insufficient landmark information depicted on a mobile map does not support wayfinding and spatial learning. An overabundance of visualized objects on the mobile map, on the other hand, frustrates navigators in searching for and remembering useful landmarks and thus leads to cognitive overload and failure in orientation and wayfinding.

Hence, to design a mobile map that supports users' spatial learning while ensuring navigation efficiency and success, it is necessary to investigate the relationship between the numbers of landmarks depicted on a mobile map, spatial learning, and cognitive load. This leads to the first two research questions (RQs) of this thesis, defined for the purpose of these text boxes as RQ:

RQ1: How does the number of landmarks depicted on a mobile map influence navigators' spatial learning during navigation?

RQ2: How does the number of landmarks depicted on a mobile map influence navigators' cognitive load during wayfinding while consulting the map?

Furthermore, previous research has demonstrated that cognitive load for one attended task may spill over to another subsequent task (Bednar et al., 2012; Felisberti & Fernandes, 2022; T. X. Liu et al., 2019). Cognitive load related to consulting landmarks and route directions displayed on a mobile map during navigation may also influence cognitive load during active locomotion through the environment, even if the navigator is not attending to the mobile map display. Similarly, the cognitive load during active locomotion may in turn affect the cognitive load during map consultation. Thus, it is also important to examine cognitive load during location through the environment separately from the phase of viewing the mobile map. This leads to the third research question:

RQ3: How does the number of landmarks depicted on a mobile map influence navigators' cognitive load during active locomotion through the environment?

1.3 Thesis approach

To investigate the three foregoing research questions, I used neuropsychological research methods. Specifically, I set out one navigation experiment in virtual reality (VR) using a within-participant design and recruited participants to complete the experiment. During navigation, participants were asked to follow a given route on a mobile map and learn landmarks in three different virtual urban environments. I visualized three sets of landmarks on mobile maps, based on the previous literature on cognitive capacity. I assessed participants' spatial learning performance after navigation in the virtual environment (RQ1), and their brain activity during wayfinding while viewing the mobile map (RQ2) and during active locomotion without consulting the map (RQ3). Participants' brain activity was recorded by a 64-channel electroencephalogram (EEG) device during the experiment.

To answer the question on how the number of landmarks depicted on a mobile map influences spatial learning during navigation (RQ1), participants' spatial knowledge was assessed immediately after each map-assisted navigation trial. Three spatial learning tests (i.e., a landmark recognition test, a route direction test, and judgments of relative directions) were used to assess landmark knowledge, route knowledge, and survey knowledge, respectively (Montello, 2011; Siegel & White, 1975; Wiener et al., 2009).

To answer the question on the effect of the number of landmarks depicted on a mobile map on cognitive load during map consultation (RQ2), participants' brain activity while viewing maps was examined using event-related brain potentials and power spectral analysis (PSA). Following the findings of previous studies (e.g., Gevins & Smith, 2003), the cognitive load was indexed by 1) theta event-related synchronization at fronto-central leads; 2) alpha event-related desynchronization at parieto-occipital leads; and 3) amplitude of a slow positive wave (i.e., P3) at parieto-occipital leads.

To answer the question on the relationship between the number of depicted landmarks and cognitive load during active locomotion in the environment without consulting the map (RQ3), participants' brain activity while moving through the environments was analyzed using eye blinks as EEG event markers. Based on the findings of previous literature on blink-related brain activity, I examined cognitive load by analyzing the blink-related N2 amplitude at frontal-central leads and the blink-related P3 amplitude at parieto-occipital leads.

The obtained spatial learning outcomes and EEG measures were tested at a level of statistical significance between the three landmark conditions using linear mixed-effects modeling.

The results in relation to RQ1 and RQ2 are reported in the journal article published by *Frontiers in Virtual Reality* in November 2022, available online: https://doi.org/10.3389/frvir.2022.981625. The results in relation to RQ3 are reported in the journal article published by *Frontiers in Neuroscience* in January 2023, available online: https://doi.org/10.3389/fnins.2023.1024583.

1.4 Relevance

Why do we still care about spatial learning and navigational skills when mobile navigation devices can take over all navigation tasks and provide all information about how to get there? Do our spatial and navigational skills still have a role to play in our lives in the face of digital transformation?

First, navigational skills and spatial knowledge are still critical to our survival in many circumstances, where GPS devices have no satellite reception, run out of battery, or malfunction in some way. Without being equipped with navigational skills and spatial knowledge, we easily experience disorientation and loss, which leads to anxiety and frustration. These circumstances due to the failure in technology can further cause extreme examples of "death by GPS" in humans, including loss of life (Aporta & Higgs, 2005).

Second, we either "use it or lose it". London taxi drivers, with intensive navigation experience and extensive spatial knowledge of the city, have a larger hippocampus than London bus drivers (Maguire et al., 2006). In contrast, if we surrender the navigation tasks to GPS technologies, our biological hardware (the related brain regions, e.g., hippocampus) and functional software (spatial skills) do not receive enough practice and become less active (Shors et al., 2012).

Moreover, spatial navigation is associated with cognitive aging (Allison et al., 2016; Coughlan et al., 2018). Emerging evidence from behavioral, cognitive, and neurological research has demonstrated that spatial orientation and navigation deficits are reliable cognitive indicators for preclinical Alzheimer's disease and mild cognitive impairment (Allison et al., 2016; Coughlan et al., 2018, 2020). The brain regions (e.g., hippocampus, retrosplenial cortex, and entorhinal cortex) involved in spatial navigation strongly overlap with the brain regions affected by AD dementia (Coughlan et al., 2018; Kunz et al., 2015).

Finally, navigation and spatial memory are one of the elements that made us human. Navigation is about more than just getting from one place to another; navigation is about life experiences and memory of those experiences in relation to space and time (i.e., episodic memories). The activations and connections inside our hippocampi enable our long-term memory—not only cognitive maps of the places we have traveled, but also the narratives of the life we have lived: people we have met, emotions we have experienced, and fantasies we have imagined (Ekstrom & Ranganath, 2018).

Therefore, in this thesis, I attempt to leverage effective map design on mobile navigation devices to complement our brain functions with the ultimate goal of supporting people's spatial memory as they navigate in environments.

Chapter 2: Related Work

2.1 Navigation and spatial learning

2.1.1 Navigation

Montello (2005) defined navigation as the coordinated and goal-directed movement of one's body through space. According to this definition, navigation consists of two major components: locomotion and wayfinding.

Locomotion refers to motor and sensory coordination and body movement through an environment (Montello, 2005). For pedestrian navigation, walking in an environment is a representation of locomotion (O'Mara, 2020). Locomotion in pedestrian navigation is critical not only for avoiding obstacles and traveling safely, but also for translating spatial information into individuals' body-based cues, such as proprioceptive and vestibular body signals, and directing our bodies to correct landmarks and routes (Montello, 2005). Locomotion thus plays an important role in self-orientation, spatial updating, and spatial memory acquisition while moving through an environment (Huffman & Ekstrom, 2021; Philbeck et al., 2001). Locomotion can be distinguished as active or passive mode (Montello, 2005). Actively locomoting individuals control their heading and speed of movement (Montello, 2005). They tend to be more visually attuned to spatial information in the environment (Frissen et al., 2011), and acquire more spatial knowledge of the environments they traverse by adapting their heading and movement, compared to their passively locomoting counterparts (Klatzky, 1998; Yan et al., 1998).

Wayfinding, on the other hand, represents the cognitive process of navigation and does not refer broadly to movement of any kind but rather to the strategic and tactical elements that direct wayfinders' movement (Darken & Peterson, 2002). More specifically, wayfinding refers to a series of planned movements and decisions in the local and distal surroundings (Montello, 2005). Wayfinding typically involves a destination place that is often located in a remote area. Humans frequently rely on internal knowledge and/or external assistance to assist wayfinding (Ekstrom & Ranganath, 2018; Wiener et al., 2009). For example, we can retrieve our internal cognitive map of the environment to reach the destination, often referred to as unaided wayfinding (Wiener et al., 2009). We can also use externalized representations to guide us along the route to the destination—this is often called aided wayfinding (Wiener et al., 2009). In fact, most everyday wayfinding cases in urban and built environments are aided by some kind of external assistance—paper maps, mobile navigation apps, and visual and verbal signage in space, to name a few (Allen, 1999). As such, the cognitive processes involved in aided wayfinding, such as planning, decision-making, and memory, are partially offloaded onto the device or signage. Therefore, the cognitive efforts during aided wayfinding could be notably different from that of unaided wayfinding (Wiener

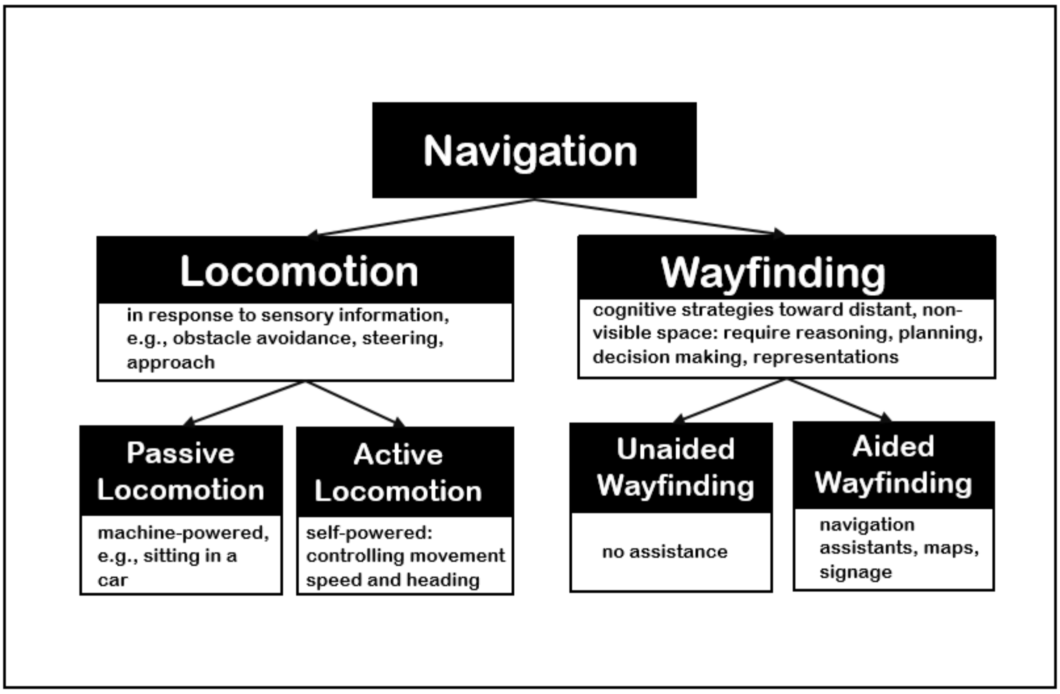


Figure 2.1 Proposed taxonomy of navigation tasks, classified by locomotion and wayfinding components (Montello, 2005). Locomotion tasks are classified by the mode of locomoting power (Montello, 2005); wayfinding tasks are classified by the existence of an external aid (Wiener et al., 2009). The figure is adapted from Wiener et al. (2009).

et al., 2009); the cognitive efforts could increase or decrease depending on the design of and/or the interaction with external assistants.

Figure 2.1 summarizes the preceding discussion in Section 2.1.1 and illustrates the taxonomy of navigation tasks and the classification of locomotion (passive vs active locomotion) and wayfinding (unaided vs aided wayfinding). The current thesis focuses on the components of active locomotion and aided wayfinding.

2.1.2 Spatial knowledge acquisition during navigation

When we navigate through space, spatial knowledge is acquired. As navigation usually involves getting to an unseen place, route planning and spatial memory of the environment occurs at every moment during navigation.

In the 1960s, developmental psychologists provided preliminary evidence that children first noticed and remembered landmarks, then learned routes by connecting these landmarks, and finally established a configuration of a series of routes (Piaget & Inhelder, 1967). This sequence of spatial representation development is supported by follow-up developmental studies (e.g., Jansen-Osmann & Fuchs, 2006; Jansen-Osmann & Wiedenbauer, 2004; Tonucci & Rissotto, 2001).

Siegel and White (1975) adopted this tripartite framework from the developmental psychologists and extended the macrogenesis of spatial knowledge acquisition (i.e., chronological skill development in childhood) to its microgenesis level (i.e., the course of spatial knowledge development during adult navigation). They classify spatial knowledge into three general aspects: landmark knowledge, route knowledge, and survey knowledge. The three types of spatial knowledge are acquired in a serial manner.

Navigators first acquire landmark knowledge: they remember the presence of prominent objects (i.e., landmarks, such as train stations and rivers) along the path in the environment. These objects can serve as beacons or points of reference for navigators. Once the landmark knowledge is achieved, navigators proceed to learn route knowledge. Route learning typically involves a sequence of decisions at intersections. This sequence is usually coded as place-action associations, such as "turn right at the church, then turn left at the school" (Chrastil, 2013; Kuipers, 1978). This sequence can be also coded in spatial and temporal information, such as "first turn right, then turn left", as most existing GPS-enabled navigation devices guide wayfinders. After the route knowledge is established, navigators then acquire survey knowledge. Survey knowledge is defined as an allocentric representation of an environment that is independent of one's own body position (Klatzky, 1998). Survey knowledge is the most sophisticated among the three types of spatial knowledge, generates an overall layout of the environment, and connects the relations between landmarks and routes. The generated cognitive map of the environment enables navigators to take novel routes and shortcuts between locations (O'Keefe & Nadel, 1978; Tolman, 1948).

The threefold stage concept from Siegel and White (1975) has been influential and has become the standard in human navigation research. However, emerging empirical evidence has challenged the stage framework by showing that all three types of spatial knowledge can be acquired in parallel, rather than in a sequential order, and that successful spatial knowledge development interacts with navigators' spatial abilities, navigational strategies, and working memory capacity (Ishikawa & Montello, 2006; Kim & Bock, 2021; Thorndyke & Hayes-Roth, 1982; Weisberg & Newcombe, 2016, 2018; Zhang et al., 2014).

For example, Ishikawa and Montello (2006) conducted a real-world navigation study and found that a few of their participants were able to acquire relatively accurate survey knowledge after only one navigation trial. Only about half of the participants gradually acquired more accurate survey knowledge with increasing exposure trials. Some participants with very poor spatial skills were unable to develop accurate survey knowledge. These results suggested that the acquisition of route and survey knowledge does not follow a strict serial order and depends on individuals' spatial abilities. A more recent study by Kim and Bock (2021) asked the participants to navigate through a virtual urban environment and then assessed their acquisition of landmark, route, and survey knowledge after each of ten wayfinding trials. The authors found that all three types of spatial knowledge gradually improved from trial to trial and suggested that the three aspects of knowledge may start out independently in the first wayfinding trial and gradually increase their interaction and cooperation during the subsequent trials.

Figure 2.2 illustrates the three categories of spatial knowledge acquisition: landmark knowledge, route knowledge, and survey knowledge, as discussed in Section 2.1.2. The thesis addresses all three aspects of spatial learning.

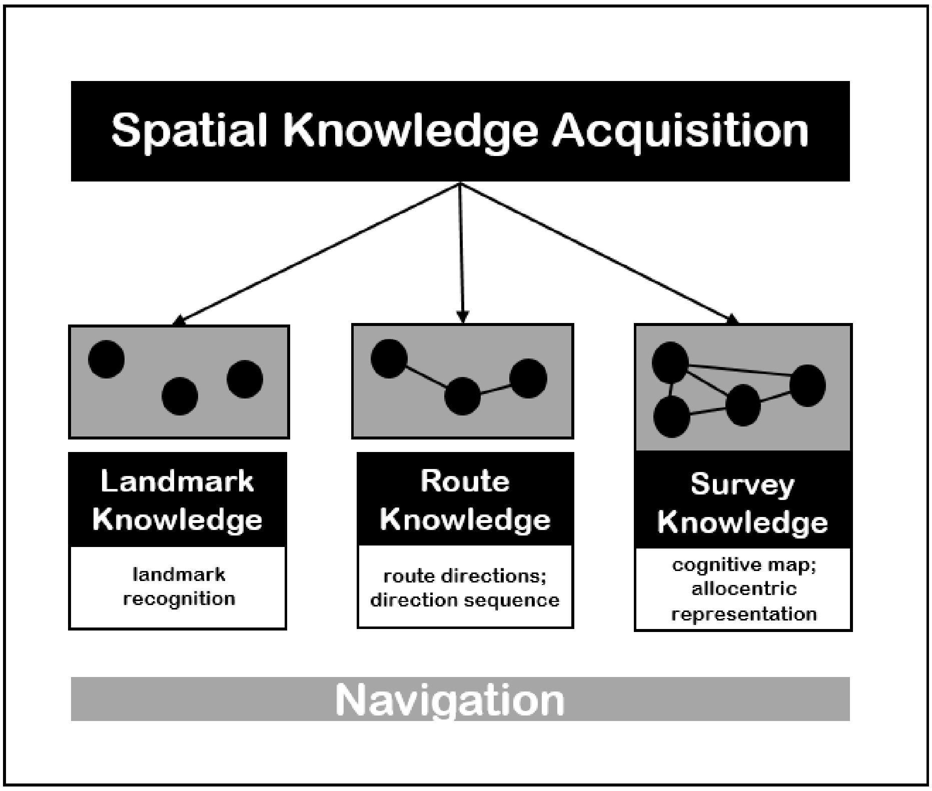


Figure 2.2 A model of three aspects of spatial knowledge acquisition during navigation. The figure provides a visual summary of Section 2.1.2. Source: own graphics. Graphics style: Wiener et al. (2009)

2.2 Navigation assistance

To aid navigation and orientation in space, humans have a long history of creating and using maps (Montello, 2002). As early as 20,000 B.C. our ancestors may have already drawn geographic features of their surroundings (e.g., mountains, rivers, and valleys) on mammoth tusks and bones (Schøyen Collection; Wolodtschenko & Forner, 2007). Ancient civilizations—Babylon (c. 600 BC), Greece (c. 611–546 BC), and China (c. 400 BC)—produced extensive maps to represent and communicate spatial information. One of the most influential maps in history was created by Henricus Martellus, a German cartographer, in 1491 (Figure 2.3). With the assistance of this map, Christopher Columbus planned his voyage and made the first crossing of the Atlantic Ocean. In a similar time period (1402-1424) but on the other side of the globe, the Chinese voyager Zheng He established the maritime Silk Road and sailed the distant seas of China, South Asia, and Africa. Zheng He's sailing routes were depicted as a set of maps and compiled as a collection of navigational maps by Mao Yuanyi in 1621, now known as the Mao Kun map (Figure 2.4).

Since the time of Columbus and Zheng, cartographic techniques and design have evolved substantially, and spatial information has been represented on a flat map more sophisticatedly, precisely, and accurately. Physical maps have been a powerful tool, helping our ancestors to explore and travel territories for centuries. Only in the past two decades,

Figure 2.3 The 1491 map made by the German cartographer Henricus Martellus. Photo by Lazarus Project / Megavision / RIT / EMEL, Courtesy of the Beinecke Library, Yale University.

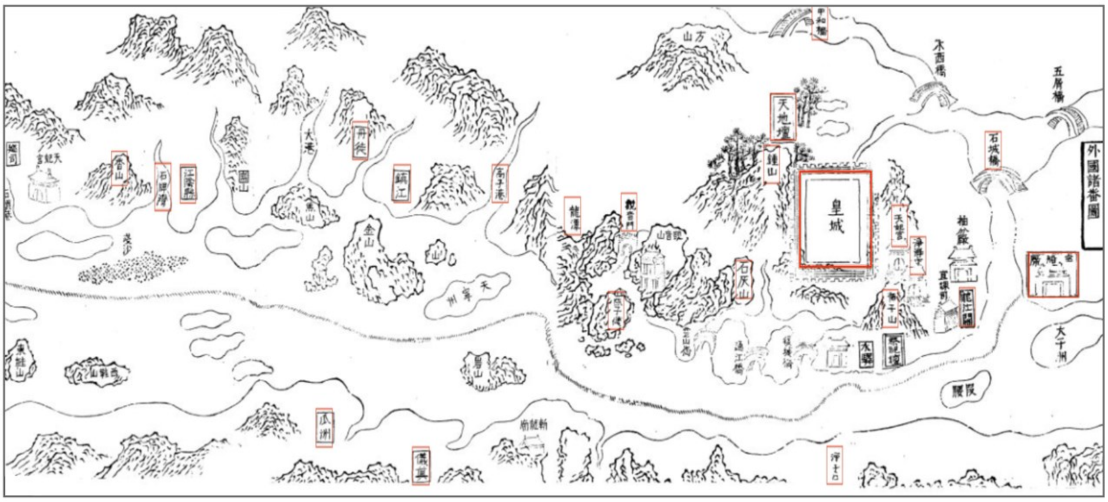


Figure 2.4 One map chart of the map collection booklet Mao Kun Map (1621). The interactive version of this map was created by Prof. Barbieri-Low, University of California, Santa Barbara.

digital and satellite technologies have transformed geographic information communication from static and paper-based maps to interactive and digital media.

Unlike our ancestors who used paper maps, in the digital era we increasingly use mobile navigation systems that are integrated with global positioning systems (GPS; Pew Research, 2011, 2015). As GPS technology has become inexpensive and can be embedded in smartphones, smartwatches, and various vehicles (e.g., bicycles, cars, boats, etc.), we use such GPS services not only for strolling in urban areas, but also for hiking in mountains, sailing at sea, and more (Montello, 2002). According to a survey in the United States in 2015, 67 percent of smartphone owners use some type of location-based service on their phones at least occasionally for navigation, while this number was 28 percent in 2011 (Pew Research, 2011, 2015). Given that the number of smartphone owners continues to grow (Pew Research, 2021), especially outside of Europe and North America, nearly everyone on the planet could soon own a GPS device (O'Connor, 2019, p. 3).

Compared to paper maps, GPS-enabled navigation devices provide us with automatic services in an instant: our locations in space can be tracked in real time without knowing where we actually are; the shortest route to a novel destination can be automatically planned and the turn-by-turn directions can be vividly presented to us; the information on and behind the small screen can be searched, zoomed in/out, and panned left/right.

However, before we get too excited about how a hand-sized GPS device can make our lives easier and more convenient, let us think twice: do such instant conveniences also take something away from us?

2.2.1 GPS use and spatial learning

In fact, abundant evidence across many disciplines has pointed out that the use of GPS-enabled navigation systems can affect navigators' attention to the environment, impair their spatial learning of the traversed environment, and degrade their spatial skills (Dahmani & Bohbot, 2020; Gardony et al., 2013, 2015; Münzer et al., 2012; I. T. Ruginski et al., 2019). Turn-by-turn directions on the screen splits navigators' attention between the device and the traversed environment and navigators pay less attention to the traveled environment (Brügger et al., 2019; Gardony et al., 2013, 2015). In addition, travelers tend to passively follow the given route shown on GPS devices and do not actively make spatial decisions at intersections (Clemenson et al., 2021; Fenech et al., 2010). As a consequence, navigators are not supported to actively encode environmental information (e.g., landmarks and routes) into their memory (Dahmani & Bohbot, 2020; McKinlay, 2016; Parush et al., 2007; M. Sugimoto et al., 2021).

Ishikawa et al. (2008) conducted a real-world study to examine the effect of GPS use on pedestrians' wayfinding behavior and spatial knowledge acquisition, compared to paper map use and direct experience of routes. The results revealed that GPS users had lower wayfinding efficiency—they traveled longer distances and more slowly and they stopped more during wayfinding, compared to map users and direct-experience wayfinders. GPS users also showed poorer spatial knowledge acquisition—they made more errors in the direction-pointing task and in the map-sketching task, compared to direct-experience wayfinders. One possible reason, suggested by the authors, for the decline in navigation efficiency and spatial learning was that the small size of the GPS screen limited effective communication of large-scale environmental information.

A cross-sectional and longitudinal study conducted by Dahmani and Bohbot (2020) established a causal relationship between GPS use and poor spatial memory in a dosedependent manner—that is, using GPS leads to a decline in spatial memory, and the greater the use of GPS, the greater the decline in spatial memory over time. The authors suggested that using GPS to navigate from one point to another removes the need to pay attention to our environments and the need to internally update our position in space as we travel.

Ruginski et al. (2019) performed structural equation modeling to examine whether and how everyday GPS use adversely affected individuals' spatial transformation abilities (i.e., perspective taking and mental rotation). The authors found that long-term habitual use of GPS negatively and directly affects spatial learning through degraded object-based (i.e., mental rotation) and egocentric (i.e., perspective-taking) spatial abilities.

2.2.2 Cartographic design of mobile map displays

The aforementioned societal problem of spatial deskilling caused by individuals' reliance on GPS technologies has caught the attention of some geographic information scientists (GIScientists) and psychologists, who have approached the problem from an interdisciplinary perspective by asking how GPS-enabled *mobile map design* influences navigators' behavior and spatial learning (e.g., Keil et al., 2020; Liao et al., 2017; Münzer et al., 2012, 2020; Stevens & Carlson, 2019).

For example, Liao et al. (2017) empirically examined different mobile map design choices with different spatial detail levels of the environment visualized on mobile maps, such as abstract 2D cartographic maps versus realistic-looking 3D satellite image maps. The results demonstrated that satellite image maps impeded spatial memory building due to visual information overload, while visualized landmarks on both types of mobile map displays benefited navigators' route direction memory at complex intersections. Münzer et al., (2012, 2020) investigated the different alignment choices of mobile maps by comparing the dynamic track-up orientation (i.e., egocentric perspective) with the static north-up orientation (i.e., allocentric perspective) of a mobile map during wayfinding. The authors concluded that the acquisition of different types of spatial knowledge, such as egocentric and allocentric spatial knowledge, can be facilitated by appropriate map visualization. Credé et al. (2019, 2020) examined different landmark visualization choices on a mobile map, such as visualizing local landmarks (located on route at intersections with or without a direction change) versus global landmarks (located off route, distant but visible from the route). The authors suggested that the depiction of global landmarks on mobile maps supported survey knowledge acquisition during navigation under stress.

Cartographers and cognitive scientists have recently proposed to counteract the negative effects of GPS-enabled navigation systems on spatial learning. Among the calls proposed, appropriate inclusion and effective visualization of landmarks on a GPS-enabled mobile map have drawn particular attention in navigation research (Duckham et al., 2010; Keil et al., 2020; J. Liu et al., 2022; Raubal & Winter, 2002; I. T. Ruginski et al., 2019; Wenig et al., 2017).

2.3 Landmarks

An early definition of landmarks by Lynch (1960) states that landmarks 1) are prominent features in an environment, 2) serve as points of reference, and 3) allow people to easily identify them from their background. This definition remains influential in landmark research. A more recent definition made by Richter and Winter (2014) refers to landmarks as cognitive anchors in an environment which help navigators to structure mental representations of the environment. This definition emphasizes the role of landmarks in space representation and in humans' minds. Stankiewicz & Kalia (2007) defined three landmark properties that help wayfinding and navigation processes: (1) *persistence*, that is a landmark should be present when navigators return to the same location later; (2) *salience*, that is a landmark should be easily detectable and identifiable from their background in an environment; and (3) *informativeness*, that is a landmark needs to provide information about the navigator's position and/or what action should be taken when observing the landmark.

2.3.1 Functions of landmarks

Landmarks are recognized to hold high practical importance for navigation and spatial learning (Epstein & Vass, 2014; Yesiltepe et al., 2021). Chan et al. (2012) discussed a taxonomy of landmark functions and presented four main functions of landmarks in spatial navigation: landmarks as 1) *navigational beacons* that indicate reliable cues to a nearby target location, 2) *orientation cues* that help navigators to stay oriented and know the direction to the target location, 3) *associative cues* that are critical for navigators to remember the traversed routes, and 4) *a frame of reference* for encoding spatial information and building survey knowledge. Ample empirical studies have provided behavioral and neural evidence and supported these proposed functions of landmarks in navigation and wayfinding (for a review of behavioral studies, see Yesiltepe et al., 2021; for a review of neural studies, see Epstein & Vass, 2014). Landmarks help navigators to determine their current location (Stea, 1973), remember key decision points on routes (Liao et al., 2017; Raubal & Winter, 2002), and navigate to a destination by accessing stored spatial knowledge of landmark relations (Ligonnière et al., 2021).

2.3.2 Landmark visualization on mobile maps

Despite the importance of landmarks for human navigation, very few existing navigation systems communicate landmarks efficiently and effectively while providing wayfinding instructions. At one extreme is that no landmark is referred to in wayfinding instructions (Raubal & Winter, 2002). For example, most existing navigation systems use turn-by-turn instructions that only refer to direction and distance (e.g., turn left in 200 meters). The omission of landmarks on GPS-enabled navigation systems could explain why these devices are often found to have a negative effect on spatial learning (e.g., Ruginski et al., 2022), as discussed in Section 2.2.1; omitting landmarks may lead navigators to overly rely on turn-by-turn route directions on the device, and to pay less attention to the surroundings. As a consequence, they cannot create a visual representation of the traversed environment and thus fail to acquire spatial knowledge of the environment (Denis & Fernandez, 2013). At the other extreme is providing too much landmark information, including all points of interest that are not even visible from the navigation route, as many commercial mobile maps do. Excessive landmark information may overload travelers and thus impede their wayfinding efficiency and spatial encoding of the environment (Liao et al., 2017; Münzer et al., 2012), given that there is *limited cognitive capacity* available to process information (Baddeley, 2003).

2.4 Cognitive capacity

Classic cognitive psychology literature has suggested that individuals have a limited capacity for information processing—typically four units (or chunks) during a task (for a review, see Baddeley, 2003; Luck & Vogel, 1997; Vogel et al., 2001). The learning performance reaches a plateau (or even drops) when the number of learning items exceeds learners' limited cognitive capacity.

According to Baddeley (2003), there are two major components in the working memory systems: verbal working memory (VWM) and visuospatial working memory (VSWM) that process verbal and visuospatial information, respectively. Landmarks seen in the environment and visualized on maps possess both visual features (e.g., color, shape, texture, etc.) and spatial features (e.g., geometries, distance, density, etc.), which require the activation of VSWM processes. Thus, VSWM has particular importance in map-assisted navigation.

2.4.1 Visuospatial capacity for real-world objects

VSWM capacity refers to the number of visual items that one is able to effectively remember in a spatial array, including the number and position of those items (Baddeley, 2003). The majority of VSWM capacity research has been done using simple and low-level visual stimuli, such as oriented lines or colored triangles on a black background. The advantage of using simple visual stimuli is that no, or minimal, background knowledge of participants is required, while at the same time invaluable insights are provided into the nature of cognitive capacity (Brady et al., 2016, 2019). Yet, in real-world scenarios, higher-level meaning and knowledge play an important role in VSWM (Brady et al., 2019). In this case, WM capacity is often not a fixed number and is dependent on the learning context. Recent literature has demonstrated that learners are able to remember a higher number of meaningful and complex real-world objects (e.g., cookies, chairs), compared to simple and meaningless visual items (e.g., colored squares; for a review, see Brady et al., 2016, 2019; Endress & Potter, 2014; Sahar et al., 2020). Brady et al. (2019) suggested that for real-world objects, VSWM stores not just individual features, but ensemble information of object features. Similarly, landmarks are real-world and meaningful entities in an environment containing multiple visual, spatial, and semantic features (e.g., color hues, shape, orientation, etc.). As such, navigators may demonstrate a different VSWM capacity while learning landmarks during naturalistic navigation.

2.4.1 Visuospatial memory in spatial navigation

In wayfinding and environmental learning, VSWM processes and maintains visual and spatial cues, such as maps, environmental features, and spatial patterns (Coluccia et al., 2007; Garden et al., 2002; Gras et al., 2013; Meneghetti et al., 2021). These features and patterns are crucial for holding and manipulating the integrated mental representations of an environment and provide the foundation for effective wayfinding (Hund, 2016; Meneghetti et al., 2021; Nori et al., 2009) and spatial learning (Blacker et al., 2017; Gras et al., 2013; Knight & Tlauka, 2018; Labate et al., 2014; Münzer et al., 2012). Moreover, navigation and spatial learning require binding visual and spatial information from different parts of the route together into temporal episodes. This is, earlier information must be maintained in VSWM, in order to bind new information to the event, such as the relational properties between places and actions that link them—route knowledge and directional relations between places—survey knowledge. Given that individuals have limited VSWM capacity, it is thus important to investigate how the different amount of information displayed on mobile maps along the route utilizes VSWM during navigation.

2.4.3 Cognitive load

When visual and spatial information is processed, learners' cognitive resources are deployed, and cognitive load is generated. Cognitive load represents the total amount of cognitive resources being exerted in the task at hand (Sweller, 1988; Sweller et al., 1998) and cognitive load theory is constructed based on working memory theory. Based on cognitive load theory, cognitive resources are available during information processing for three different types of cognitive load (Chandler & Sweller, 1991; Sweller, 1988; Sweller et al., 1998). Intrinsic cognitive load is related to the nature of the task itself. In a navigation task, a traveler's intrinsic cognitive load is induced by locomotion and wayfinding processes, such as avoiding obstacles for safe locomotion and visually scanning the route to search for the correct directions. Extraneous cognitive load is generated when cognitive resources are operated for irrelevant information, such as irrelevant pop-ups on the mobile map device during map-assisted navigation. Germane cognitive load is associated with learning relevant information during the task, such as learning landmarks that are relevant to the navigation task. For example, a traveler learns the landmarks to stay oriented (e.g., a high tower visible along the route) during wayfinding or to remember the linked route direction (e.g., turn left at the museum).

2.4.4 Cognitive load measurement

Cognitive load during navigation has been mostly assessed by three different measurements in the literature (e.g., Armougum et al., 2019). The first refers to behavioral measures by evaluating behavioral performance. Such experiments commonly adopt a dual-task paradigm, in which case participants complete a secondary (working memory) task while navigating through an environment. The different levels of working memory tasks are used as a manipulation of the different levels of cognitive load, and their effects on navigation and spatial learning performance (i.e., behavioral performance) are examined (Meneghetti et al., 2021). The second is related to subjective measures, namely self-reported cognitive load (e.g., NASA-Task Load Index, Hart & Staveland, 1988). Participants are explicitly asked about their subjective cognitive load after completing the task (Armougum et al., 2019). The third refers to physiological measures, including electroencephalography (EEG), eye tracker, and electrodermal activity (EDA), which measures brain activity, eye movement, and skin conductance response, respectively. During the experiment, participants are equipped with a device to track their physiological signals while completing the navigation task.

Physiological measures have the advantage of capturing cognitive load during navigation in real time without interrupting the spatial learning and navigation processes, compared to the self-report questionnaires and the dual-task paradigm. Among the physiological measures, EEG allows neural activity in the brain to be directly assessed with high temporal resolution (milliseconds), and precisely captures the dynamics of cognitive processing. Thus, EEG is a more sensitive and precise approach to understanding the cognitive processes and their subcomponents, compared to behavioral, subject, and other physiological measures.

2.5 Electroencephalography (EEG)

EEG is an established method to measure human electrocortical activity and allows brain dynamic features to be assessed without interrupting the task at hand. EEG data reflect rhythmic neural oscillations that are fluctuations in the excitability of populations (e.g., tens of thousands) of neurons (Cohen, 2014). Synchronous activation across the populations of neurons generates powerful electrical fields that can be captured by EEG electrodes placed outside the head (Figure 2.5 A). The electrodes placed in different positions on the head can capture the brain activity in the corresponding cortical regions (Figure. 2.5 B). For decades, EEG has been employed to assess different cognitive processes, such as visual processing (Y.

K. Wang et al., 2018), working memory processing (Maurer et al., 2015; Onton et al., 2005), spatial orienting (Gramann et al., 2010, 2021), and spatial learning (Gehrke et al., 2018).

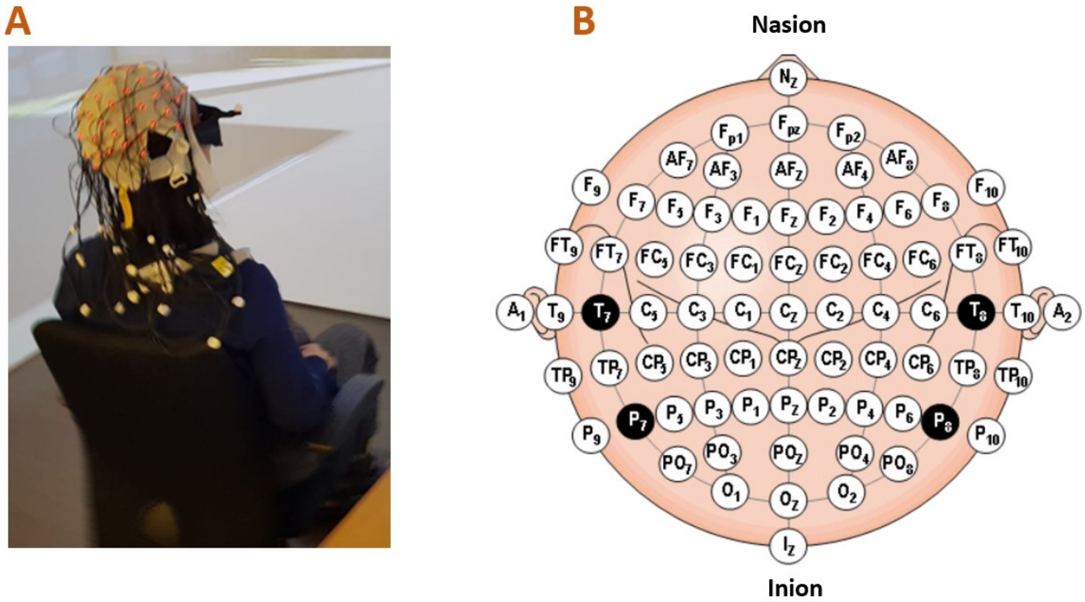


Figure 2.5 A) A 64-channel EEG headset measures a participant's brain activity during a task. B) Nomenclature of the 64 EEG electrodes displayed on a head diagram; from Nasion to Inion are: Fp, Fronto-polar; AF, Anterior-frontal; F, Frontal; FC, Fronto-central; C, Central; CP, Centro-parietal; P, Parietal; PO, Parieto-occipital; O, Occipital. Picture A is credited to Bingjie Cheng; Picture B is adapted from Tang et al. (2019), https://doi.org/10.31083/j.jin.2019.01.103 .

2.5.1 Event-related potentials (ERPs)

ERPs analysis is a well-established and powerful EEG analysis method to investigate cognitive processing. ERPs represent neural responses to specific events during a task (Fu & Parasuraman, 2006). The ERPs are computed as an average of event-locked EEG sample points across these events. These EEG events can be stimulus presentations (e.g., pictures, sounds, etc.) or participant responses (e.g., a mouse click, a button press, etc.).

Figure 2.6 depicts the process of obtaining ERPs in EEG activity (Ghani et al., 2020). Figure 2.6 A shows a typical EEG waveform with event markers (i.e., auditory tones). The waveforms in the orange windows represent the brain activity responding to the events. As depicted in Figure 2.6 B, the event-locked EEG data is averaged across multiple EEG channels and across all the event windows. This results in an event-locked grand average ERP waveform illustrated as a solid black line in Figure 1 B. The step of averaging event-locked EEG sample points can average out the invariant components covarying with the cognitive processes of interest (e.g., stimulus processing) and can cancel out random electrical noise as well as enhance reliability and statistical power (Luck & Gaspelin, 2017). Figure 2.6 C illustrates the ERP components, including N1, P2, and P3, in the ERP waveform. ERP components are generally named using the polarity (N for negative and P for positive) and then either the order (1 for the first, 2 for the second, etc.) or the average expected latency of a specific component in the ERP waveform (Woodman, 2010). The N1 (or N100) component represents the first negative potential with an expected latency of around 100 ms: approximately 100 ms in the auditory cortex or around 160 ms in the visual cortex after stimulus onset (Näätänen, 1992).

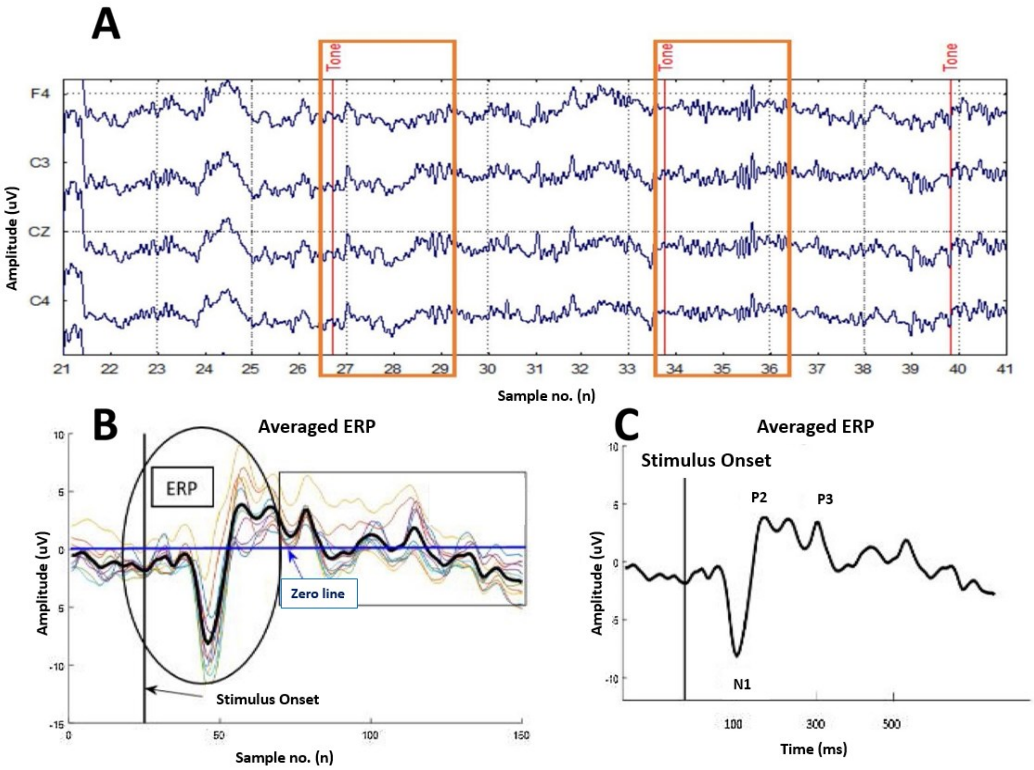


Figure 2.6 Panel A plots the EEG signals with the marked events (tones) and the event-locked time windows in the orange rectangles. Panel B plots the ERP waveform averaged across all event windows after the stimulus onset. Panel C plots the ERP components (N1, P2, P3) in an ERP waveform. The figure is adapted from Ghani et al. (2020).

The P2 (or P200) component is the second positive deflection with a peak latency of around 200 ms. The P3 (or P300) component is a relatively large and slow positive-going component with a peak latency of around 300–800 ms (Watter et al., 2001). The early ERP deflections that appear before 50 ms represent evoked neural activity and are relatively insensitive to changes in the psychological states of the participant. The later components are associated with the significance of a stimulus and the cognitive demands of a task (Hillyard & Kutas, 1983; Hillyard & Picton, 2011). These "endogenous" ERP components have been researched widely in different settings as indices of specific modes or stages of information processing. In the visual modality, participants attending to the visual and spatial stimuli in the visual field elicit ERP waves between 100 and 300 ms after stimulus, including N1 and P2, distributed over the occipital and parietal areas (Hillyard & Kutas, 1983; Hillyard & Picton, 2011). These ERP components likely reflect an early bottom-up selective attention mechanism that directs attention to the focused visual field. The late positive P3 component, one of the most studied components, has been considered to respond to the later top-down stage of selective attention and other cognitive processing, including memory storage and retrieval, decision-making, and linguistic processing (Hillyard & Kutas, 1983; Hillyard & Picton, 2011).

2.5.2 Frequency-domain analysis

In contrast to ERPs looking at the time-domain EEG signals, frequency-domain analysis leverages frequency decomposition techniques, such as Fast Fourier Transform (FFT), to convert time-domain EEG signals (amplitude versus time) to frequency-domain signals (amplitude versus frequency; (S. Liu et al., 2021). The frequency-domain analysis is also known as spectral analysis. Among all spectral methods, PSA is used most commonly, because power spectral density is a straightforward way to reflect the distribution of signal power over frequency (Dressler et al., 2004). Changes in the power spectrum reflect changes in oscillations of neurons at different frequencies and thus represent different aspects of cognitive-affective processes (Hudspeth & Pribram, 1990). The major oscillatory components in the EEG power spectrum and their frequency ranges are identified as follows: delta (1-3.9

Hz), theta (4-7.9 Hz), alpha (8-12.9 Hz), and beta (13-29.9 Hz). Figure 2.7 shows the different neural oscillations and their assigned frequency ranges. To note, the precise frequency ranges of the different oscillatory components continue to be under debate.

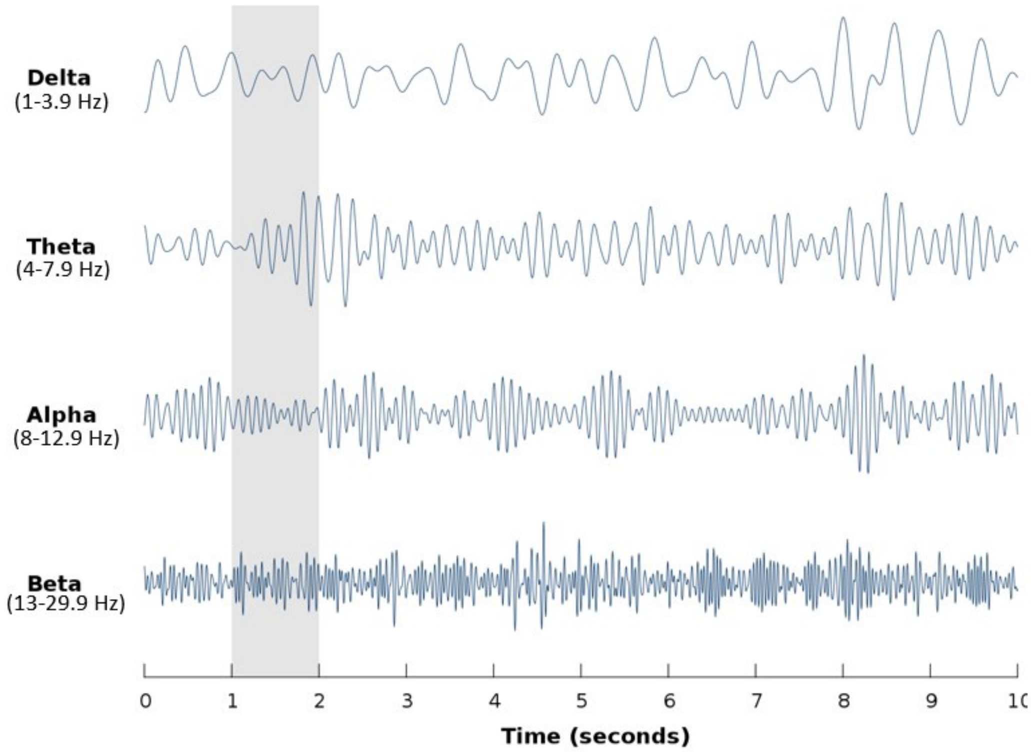


Figure 2.7 Four frequency bands of neural oscillations (i.e., delta, theta, alpha, and beta) and their assigned frequency bands, as shown in the ten seconds of the EEG signal. The figure is adapted from https://en.wikipedia.org/wiki/Neural_oscillation

2.5.3 Visual and spatial encoding measured by EEG

Visual and spatial encoding manifests through the modulation of components in ERPs. Previous ERP literature has found that the early ERP component P1/N1 amplitude measured at the parietal and occipital regions frequently underlies early visual and spatial attention (for a review, see Fu & Parasuraman, 2006). For example, S. A. Hillyard and Anllo-Vento (1998) provided empirical evidence that the P1/N1 is associated with the early visual encoding of the presented stimuli, and its amplitude in the occipital region increases with greater visual attention allocation to these visual stimuli. In one study by Awh et al. (2000), the amplitude of the posterior P1/N1 has been shown to increase with the increasing load of encoding objects' spatial locations.

Visual and spatial information encoding also manifests in power modulations of neural oscillations. EEG studies have found that larger theta oscillations in the parietal and occipital leads are often elicited by spatial and visual information encoding, respectively. The increased theta oscillations in the parietal region have been shown to implicate spatial information processing during computerized spatial tasks with simple stimuli (Moran et al., 2010; White et al., 2012) as well as during naturalistic spatial navigation tasks in visually complex and ecologically valid environments (Bohbot et al., 2017; Delaux et al., 2021; Do et al., 2021). Neuropsychological evidence has suggested the theta oscillations in the parietal cortex during spatial navigation result from the oscillations in subcortical regions related to spatial memory encoding, such as retrosplenial complex (RSC) and hippocampus (Bohbot et al., 2017; Do et al., 2021; Epstein & Vass, 2014).

Increased theta oscillatory activity in the occipital region has been shown to be associated with visual encoding and visual attention to presented stimuli (Gladwin & De Jong, 2005; McDermott et al., 2017; Y. K. Wang et al., 2018). By contrast, decreased power of alpha oscillations in the occipital region has been frequently found during visual and spatial encoding (Delaux et al., 2021; Klimesch et al., 1998; Nelli et al., 2017; Y. K. Wang et al., 2018).

2.5.4 Cognitive load measured by EEG

Cognitive load has been extensively studied in neurophysiological research (Fu & Parasuraman, 2006; Ghani et al., 2020; Kok, 2001; Polich, 2007). A large body of ERP research has suggested that posterior P3 amplitude is proportional to the intensity of a task on attentional and working memory resources and reflects cognitive load (for a review, see Fu & Parasuraman, 2006; Ghani et al., 2020; Kok, 2001; Polich, 2007). That is, more pronounced P3 amplitude in the parietal region is induced by greater task difficulty and greater stimulus complexity presented to participants (Ghani et al., 2020; Kok, 2001; Polich, 2007; Watter et al., 2001). The relationship between P3 amplitude and cognitive load is studied in single-task and dual-task paradigms (Deeny et al., 2014; Ghani et al., 2020). In the single-task paradigm, participants focus on one primary task and are probed with different task difficulties, which can provide a more straightforward cognitive load estimation, compared to dual-task paradigms (Deeny et al., 2014; Ghani et al., 2020). For example, in attention-focused paradigms, P3 amplitude was greater when participants paid attention to target stimuli compared to unattended stimuli (Heinze et al., 1990; Van der Stelt et al., 1998). In contrast to single-task paradigms, dual-task paradigms provide a window to examine attentional resource allocation between tasks. In dual-task paradigms, participants perform a primary task as well as a secondary task. Studies have found that the P3 amplitude evoked by the secondary task decreases with the increasing difficulty of the primary task, indicating a reallocation of attentional resources away from the secondary task to the primary task (Isreal et al., 1980; Watter et al., 2001).

Previous EEG research has found that cognitive load also manifests in power modulations in distinct frequency bands, especially in theta and alpha bands (for a review, see Klimesch, 1999). A large body of research has shown that task demands, visual attention, and visual working memory evoke theta oscillations and suppress alpha oscillations (Gevins & Smith, 2003; Jensen & Tesche, 2002; Ratcliffe et al., 2022; Scharinger et al., 2017; Smith et al., 2001). A method calculating event-based synchronization (ERS) in theta oscillations and event-based desynchronization (ERD) in alpha oscillations is used to compute task-related changes in the synchrony of underlying neuron populations (Pfurtscheller & Lopes da Silva, 1999). A number of studies have found that theta ERS recorded over the frontal cortex responds to visual stimulus presentation, implicating increasing cognitive resource expenditure (Ratcliffe et al., 2022; Scharinger et al., 2017; Smith et al., 2001). Specifically, theta oscillations are related to the integration and control of a variety of cognitive processes, such as visual and spatial working memory (Sauseng et al., 2010). Thus, theta ERS in frontal leads has been proposed as a neural indicator of cognitive load. Previous studies, by contrast, have found that the more demanding a task, the more pronounced is the alpha suppression or

ERD in parietal leads (Doesburg et al., 2009; Stipacek et al., 2003). Alpha ERD in parietal regions may implicate participants' maintenance of attention and working memory during a cognitive task (Fukuda et al., 2015; Pfurtscheller et al., 1996; Sauseng et al., 2005).

2.5.5 Examining brain activity during locomotion

Cognitive load induced by one attended task may spill over into another successive task, as shown in the literature (Bednar et al., 2012; Felisberti & Fernandes, 2022; T. X. Liu et al., 2019). For example, Felisberti and Fernandes (2022) have found that participants' cognitive load spilled over to subsequent tasks, in which they completed a simulated driving task in virtual environments. Similarly, during map-assisted navigation, the cognitive load related to viewing and learning landmarks depicted on a mobile map may impact cognitive load during locomotion through the environment, even if the pedestrians are not looking at the mobile map display. Furthermore, as discussed in Section 2.1, navigation consists of both a locomotion and a wayfinding component (Montello, 2005). Pedestrians spend most of their time in locomotion through the environment during navigation, compared to viewing a map. Moreover, map-assisted navigation consists of dynamic interaction between the user, the map, and the environment (see Figure 2.8). To attain a holistic understanding of navigators' cognitive states during map-assisted navigation, it is also important to examine users' cognitive load and visual encoding while they are locomoting in the environment while not consulting a mobile map. As discussed in Section 2.4.1, EEG recordings typically require event markers such as stimulus presentation or participant responses to allow event-related analysis. This is challenging in a naturalistic navigation context because visual inputs to navigators constantly change when they actively move through the environment, which results in little control over stimulus presentation or participant responses during EEG recordings. As such, new types of EEG markers are required to investigate brain activity during naturalistic locomotion.

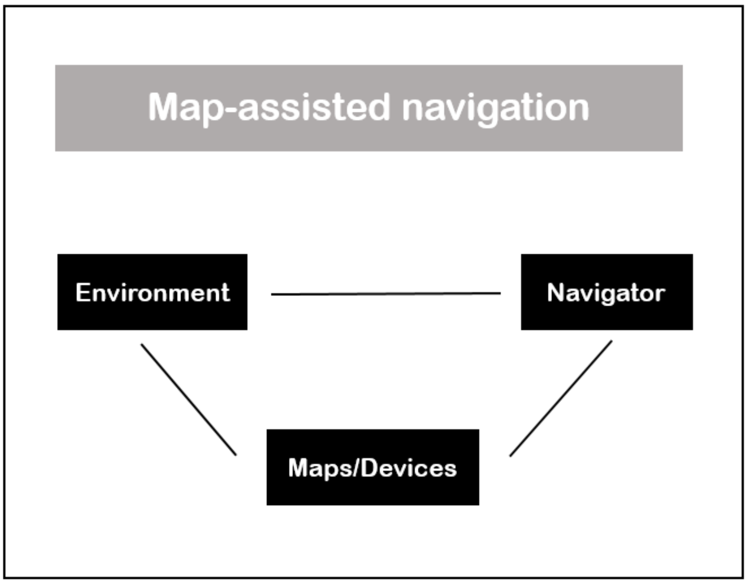


Figure 2.8 Interaction between the mobile map, the navigator, and the environment during map-assisted navigation. Each component needs to be considered and evaluated when discussing map-assisted navigation. Figure adapted from Ishikawa (2020, p. 157).

Eye blinks as EEG events during naturalistic locomotion

Researchers have leveraged spontaneous eye behavior—gaze fixation and blinks—during EEG recordings and used it to generate notable EEG event markers and examine the related brain activity. A recent study used navigators' gaze fixation on indoor navigational signs indicating directions (e.g., ambulatory care unit, information desk, etc.) as EEG event markers, to investigate the effect of interior designs (e.g., color patterns, graphics) on wayfinding efficiency in a virtual hospital (Kalantari et al., 2022). Such event markers (i.e., gaze fixation) are useful for wayfinding experiments in environments containing task-relevant signage used during wayfinding. This will generate long fixation durations (e.g., 1500 ms) as meaningful EEG event markers. Nevertheless, outdoor environments have little explicit labeling and/or navigation-relevant signage in open spaces, such as parks and residential areas, where pedestrian navigators yield shorter fixation duration (~290 ms; Enders et al., 2021).

Using spontaneous eye blinks is another way to create useful event markers without interfering with the continuous tasks in naturalistic settings (Wascher et al., 2014, 2016, 2022), given that eye blinks are generated by participants naturally and can be easily detected by EEG without an additional device. Moreover, eye blinks could be used as meaningful EEG event markers indicating cognitive load, as previous literature has suggested that spontaneous eye blinks do not occur randomly, but are considered to reflect cognitive load and information processing (Siegle et al., 2008; Stern et al., 1984). When participants open their eyes after a blink, they receive an influx of visual and spatial stimuli. This leads to the engagement of cognitive resources for visual and spatial working memory and elicits brain activity related to cognitive processing (Fukuda et al., 2015; Lee et al., 2018). A study by Valtchanov and Ellard (2015) analyzed participants' eye-movement behavior when they were viewing photographs of nature and urban scenes. The authors found that participants' lower blink rates were associated with a lower cognitive load during nature scene viewing, compared to urban scenes. Other literature has also proposed that blinks are associated with attentional resource allocation (Wascher et al., 2014, 2022). Blinks tend to occur after blink suppression when individuals have focused attention on presented stimuli or when their processing modes change and re-allocate their attention.

Blink-related brain activity

Previous research that assesses brain activity using eye blinks as event markers has identified that ERPs appear after eye blinks (Berg & Davies, 1988; Wascher et al., 2014, 2022; Wunderlich & Gramann, 2020). Specifically, blink event-related potentials (bERPs), including blink-related occipital N1—around 160 ms after blink maximum, fronto-central N2—around 200 ms after blink maximum, and parietal-occipital P3—around 300 ms after blink maximum, can discriminate different levels of task demands.

For example, a recent study by Wascher et al. (2022) analyzed bERPs during different tasks (task load: standing < walking < walking while traversing obstacles) when participants were processing auditory information (i.e., the primary task). The results demonstrated a more pronounced amplitude in the blink-related occipital N1 in the walking condition, compared to standing and traversing obstacles, indicating more pronounced bottom-up visual processing. Furthermore, the amplitude in the blink-related N2 at the fronto-central leads and in the blink-related P3 amplitude at the parietal leads reduced with increasing task load, suggesting that fewer cognitive resources were available for the primary task (i.e., processing auditory information). The blink-related fronto-central N2 has been suggested as an indicator of cognitive control and task demand (Wascher et al., 2014, 2022). The blink-related posterior P3 has been proposed as an indicator of cognitive resource allocation (Wascher et al., 2014, 2022). In the domain of frequency power changes, two blink-related EEG studies conducted by Wascher et al. (2016, 2022) found that fronto-central theta power increased and parieto-occipital alpha power decreased with increasing task demands.

In this thesis, I leveraged spontaneous eye blinks as EEG event markers to brain activity and cognitive states during active locomotion in ecologically valid urban environments.

2.6 Virtual reality as a tool to investigate naturalistic navigation

Studying naturalistic navigation and recording EEG during navigation in the real world are challenging, because there is little control over individual factors (e.g., participants' familiarity with the environment, walking speed, etc.) and external environmental factors (e.g., traffic, weather, etc.) in real-world settings. To tackle these challenges, VR has been adopted over the last decades.

VR has the following unique advantages for spatial navigation research. First, it displays three-dimensional (3D) dynamic images with high quality (Sanchez-Vives & Slater, 2005) and reproduces real-life environments. In addition, researchers can manipulate environmental features based on their research questions. For example, researchers can create a novel environment, augment specific landmarks at specific locations, and easily compare environmental styles (e.g., urban versus natural; grid-like versus curvilinear roads). This is virtually impossible in the real world. The environments and the tasks created in VR can be openly shared, such as Virtual Silcton (Weisberg et al., 2014), which enhances the replicability of navigation studies (Jeung et al., 2022).

Another important feature of VR technology is that it provides naturalistic experiences and sensory feedback by integrating with locomotion interfaces (e.g., joysticks, foot pedals, treadmills, etc.) or even real-walking during navigation (Gramann, 2013). This is crucial for navigation research, as navigation is an embodied experience and active locomotion is its major component. Moreover, VR technology is compatible with physiological and neuroimaging tools, such as EDA (Armougum et al., 2019), EEG (Delaux et al., 2021), and functional magnetic resonance imaging (fMRI; Maguire et al., 2006).

With these unique characteristics, VR offers high ecological validity for investigating naturalistic navigation processes (Darken & Peterson, 2002; Jeung et al., 2022). Indeed, previous research has reported that cognitive load (Armougum et al., 2019)), navigation strategy (Clemenson et al., 2021)), and spatial knowledge acquisition (Pastel et al., 2022) in virtual environments are fairly correlated with those aspects in the real world.

2.7 Summary

To summarize this chapter, navigation and spatial learning are two closely related processes. As individuals locomote and find their way through an environment, they acquire spatial knowledge, including landmark, route, and survey knowledge. The acquired spatial memory in turn supports navigational processes. GPS-enabled navigation devices provide many conveniences that ease navigation tasks (e.g., automatic self-localization and route planning), but on the other hand, they impair spatial learning by reducing navigators' active spatial decisions, and their attention to and memorization of the environment. To counteract the negative consequences of GPS use on spatial learning, landmark inclusion is proposed to design a cognitively assistive navigation system. Navigation literature shows that landmarks bestow properties and functions that help navigators to structure and learn an environment.

Meanwhile, cognitive psychology literature suggests a limited cognitive capacity to process presented information, and a learning performance plateau/decline when the learning items exceed a learner's capacity. As map-assisted navigation and landmark memorization utilize visual and spatial processing resources, one unexamined yet important research gap arises: what is the usable amount of landmarks to present to a navigator to optimize their cognitive resource exertion and thus support spatial learning? To tackle this research gap, an accurate measure of cognitive load and visuospatial processing during navigation is crucial. EEG is a well-established neurophysiological tool to measure cognitive load and visuospatial processing, through two commonly used EEG analysis techniques: ERP analysis and PSA. To facilitate the navigation experiment equipped with EEG, VR technology offers the unique advantages of stimulating naturalistic environments and integrating body and motion cues.

Chapter 3: Experiment

The literature and research reviewed in Chapter 2 laid solid theoretical and methodological foundations for designing a hypothesis-driven and empirical navigation experiment that aims to address the research gap—what is the "appropriate" number of landmarks visualized on a mobile that optimizes navigators' cognitive resource exertion and, therefore, their spatial learning. This research gap is distilled into three concrete research questions in Chapter 1, which are revisited in the following sections along with three related hypotheses. With this research gap in mind, I first determined the independent and dependent variables for my experiment.

3.1 Independent and dependent variables

I determined the independent variable in the experiment—the number of landmarks visualized on a mobile map during assisted navigation. I chose three, five, and seven landmarks as the induction of low, medium, and high cognitive load, respectively. The selection of the three sets of landmarks was based on the cognitive psychology literature, which suggests that individuals' cognitive capacity is around four items/chunks (Baddeley, 2003) and that their memory capacity may be higher for real-world objects (Brady et al., 2016, 2019), as discussed in Section 2.4. A within-participant design was adopted to reduce inter-subject variability and produce more statistical power for the dependent variables compared to a between-subject design. The dependent variables consisted of navigators' spatial learning performance after navigation, cognitive load, and visuospatial encoding during map consultation and during active locomotion. The details of the measurements of the dependent variables are presented in a subsequent section (Section 3.5).

In the next section, I revisit the three research questions mentioned in Chapter 1 and form the hypotheses, based on the findings of the literature on navigation, cognitive psychology, and neuroscience, reviewed in Chapter 2.

3.2 Hypotheses

RQ1: How does the number of landmarks depicted on a mobile map influence navigators' spatial learning during navigation?

H1 (Spatial learning): I expected navigators' spatial learning to be improved when the number of landmarks depicted on the map increases from three to five, because of the benefits of landmarks in spatial learning. I also hypothesized that depicting seven landmarks would exceed navigators' cognitive capacities and thus counter the benefit of presenting landmarks on the mobile map. Thus, participants' spatial learning would not be expected to further increase when the number of landmarks increased from five to seven.

RQ2: How does the number of landmarks depicted on a mobile map influence navigators' cognitive load and visuospatial encoding while consulting the map during wayfinding?

H2.1 (Cognitive load): I expected that when participants consulted the mobile map, 1) P3 amplitude at parieto-occipital leads would increase; 2) theta ERS would increase at fronto-central leads; and 3) alpha ERD at parieto-occipital leads would be more pronounced along with increasing numbers of landmarks presented on the mobile map. This is because navigators' cognitive load increases when they have to process more landmarks.

H2.2 (Visuospatial encoding): I expected theta ERS in posterior leads to increase, and P1 amplitude and alpha ERD in occipital leads to be more pronounced during map consulting. This is because navigators have to encode more visuospatial information when more landmarks are depicted on the mobile map.

RQ3: How does the number of landmarks depicted on a mobile map influence navigators' cognitive load and visuospatial encoding during active locomotion?

H3.1 (Cognitive load): Due to cognitive overspilling between map consultation and active locomotion, I expected that depicting more landmarks on a mobile map would increase navigators' cognitive load during active locomotion even when they are not currently viewing the map. Increased cognitive load during active locomotion would be indicated by blink-related ERP (bERP) components—a more pronounced N2 amplitude at fronto-central leads and a more pronounced P3 amplitude at parieto-occipital leads. As an exploratory analysis on increased cognitive load, I additionally expected that blink-based theta power at fronto-central leads would increase and blink-based alpha power at parieto-occipital leads would decrease with increasing numbers of depicted landmarks.

H3.2 (Visual encoding): I expected no difference in blink-related N1 amplitude at the occipital lead, which indicated no difference in early bottom-up visual encoding, as navigators traverse through the identical environment. This is because the number of assessed landmarks only differs on the mobile map displays and not in the traversed environments.

To empirically test the above-mentioned hypotheses, I designed an experiment on map-assisted navigation. In the section that follows, I first discuss the concrete experimental manipulation of landmark presentation on a mobile map (i.e., the independent variable) during a navigation task. Next, I guide readers through the experimental stimuli and apparatus used to set up the navigation experiment in a VR lab, followed by the experimental measurements to assess spatial learning performance and brain activity—the dependent variables. Finally, I describe the profiles of tested participants and the overall experimental procedure. The following sections are intended to provide readers with a clear picture of the experiment conducted and to enable researchers to replicate or extend the experiment for future research.

3.3 Experimental design

3.3.1 Landmark presentation on a mobile map

The within-participant independent variable was empirically manipulated as the number of 3D landmark buildings (three, five, or seven) visualized on the map during navigation (Figure. 3.1). Participants navigated the routes through three different virtual cities. Each navigation route consisted of five intersections and seven salient 3D buildings as landmarks: one building at the start location (home), five salient buildings at the five intersections, and one landmark building at the destination (Figure 3.1). While participants were navigating, a map would appear on the screen at various locations along the route, simulating a view of a mobile map and showing the direction to take at the upcoming intersection (Figure 3.2).

In the three-landmark condition, the starting building, one building at the destination, and the landmark at the third intersection were visualized on the mobile map (Figure 3.1: Three-landmark condition). In the five-landmark condition, in addition to the three buildings in the three-landmark condition, one landmark at the first and fourth intersections were also displayed on the map, respectively (Figure 3.1: Five-landmark condition). In the seven-landmark condition, in addition to the five landmarks in the five-landmark condition, one landmark at the second and fifth intersections were displayed on the mobile map, respectively (Figure 3.1: Seven-landmark condition). The selection of landmarks followed the three criteria defined by Stankiewicz & Kalia (2007): persistence, salience, and informativeness, as discussed in Section 2.3.1. The building positions for each landmark condition were selected to ensure an equal spatial distribution of landmarks along the route. Figure 3.1 below depicts the three-landmark conditions along the predefined route (i.e., the black line depicted in the figure) in three different virtual environments, labeled as City 1, City 2, and City 3 in the figure.

The three navigation routes, as depicted in Figure 3.1, consisted of five intersections with lengths between 800 m and 900 m. The selected route in City 1 consists of two left turns, two right turns, and one straight intersection. The selected route in City 2 consists of one left turn, two right turns, and two straight intersections. The selected route in City 3 consists of one left turn, one right turn, and three straight intersections.

A certain route and seven selected landmarks along the route in the environment were linked to a certain city. The three landmark conditions were not linked to a certain route or a certain city. The three landmark conditions were assigned to a certain city with a counterbalanced approach.

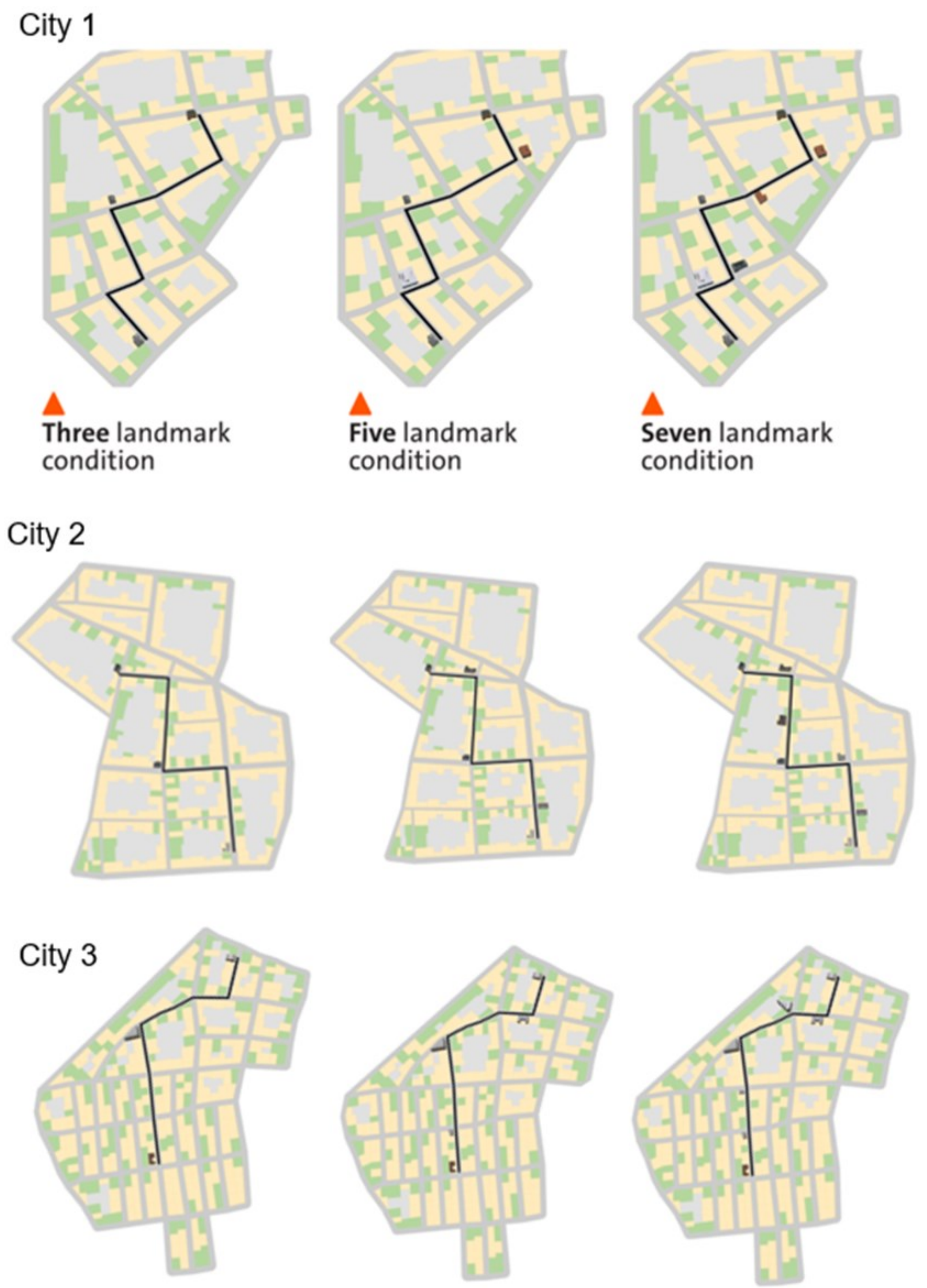


Figure 3.1 The three different landmark conditions along the predefined route (i.e., the black line) in three different virtual environments. The left, middle, and right panels show the condition with three, five, and seven landmarks depicted on the mobile map during navigation, respectively. The figure is adapted from Cheng et al., (2022).

3.3.2 Mobile map display during navigation

During navigation, a mobile map was displayed to participants to assist their wayfinding during the experiment (Figure 3.2). The mobile map that showed a predefined route and a landmark located at the intersection was presented to participants 17 times, distributed over three different location types: shortly before intersections, after intersections, and in the middle of a straight segment of the followed route, where the next intersection was visible (Figure 3.2 a, c). The map viewed from the participants' perspective during navigation is depicted in the right panel of Figure 3.2 (b, d). The map indicated the current intersection and rotated along the direction in which participants were headed. It also showed participants' current location and provided turn-by-turn directions, depicted as a blue dot and a black line on the map, respectively. Depending on the landmark condition, a visually salient landmark (Figure 3.2 d) at the intersection was shown on the mobile map. The highlighted landmark was shown in 3D on the map, with the same viewing perspective as seen in the environment (Figure 3.2 d).

The mobile map was shown for five seconds each time. When the map was displayed, the virtual urban environment faded away, and the participants' movements through the environment were disabled. This was designed to simulate a real-life scenario of mobile map consultation during pedestrian navigation. Figure 3.3 shows the sequence of participants' interaction between navigating in the environment and viewing the mobile map. The 17 map-onset events during navigation were used for event-related EEG analyses, which are discussed in detail in Section 4.2.2.

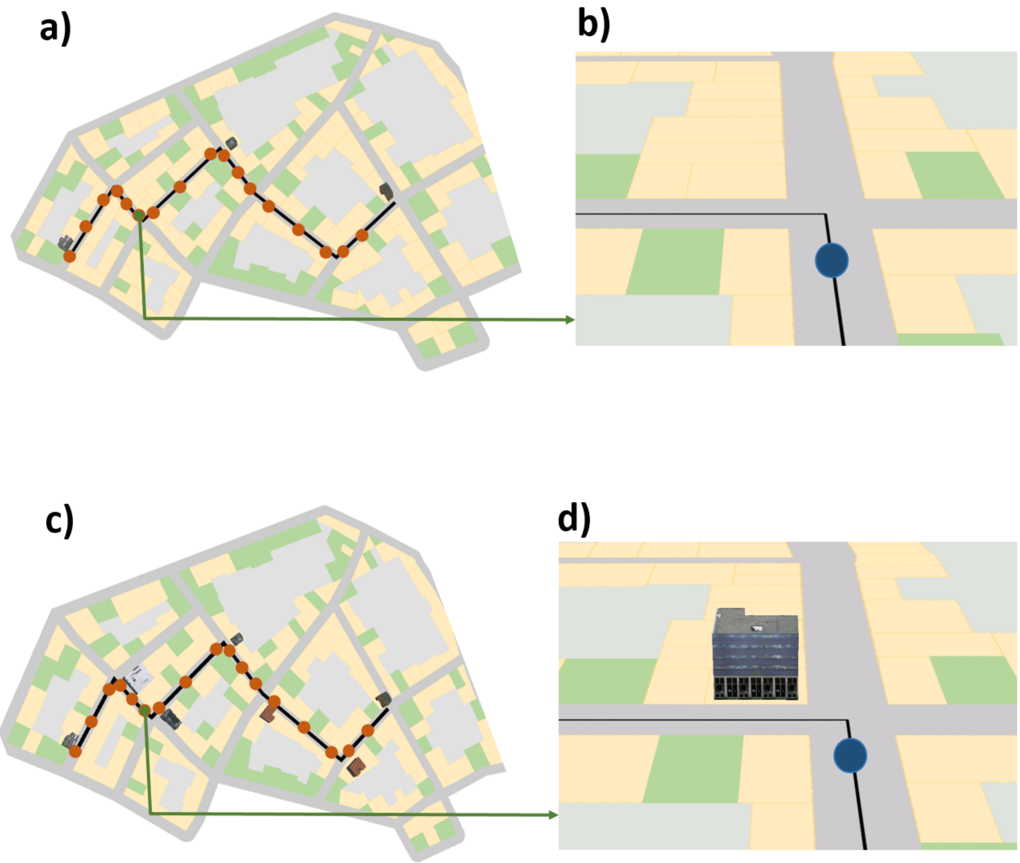


Figure 3.2 The left panel, (a) and (c), represents the map condition with three landmark and seven landmarks, respectively. Red dots along the black navigation route indicate the 17 map pop-up spots during navigation. The right panel, (b) and (d), shows a mobile map presented to the participants during navigation. The map rotates along with the participant's head direction, as seen by the participant at the location of the green dot in the left panel. The blue dot indicates the participant's current location in the virtual city. The black line indicates the path the participant needs to follow. A highlighted 3D landmark building (d) of the building is shown on the map at a turning intersection, depending on the landmark condition.

Figure 3.3 The three panels illustrate the sequence in which the participant 1) approaches the intersection in the virtual environment before the map is provided, 2) views the map for five seconds, and 3) turns at the intersection after viewing the map.

3.4 Stimuli and apparatus

To simulate real-world navigation in naturalistic environments, three ecological virtual cities were created and a navigation task was implemented in a VR lab. The details of the designed virtual cities, VR lab, and the apparatus used in the lab are presented below.

3.4.1 Virtual cities

Three European-style urban city models for navigation were developed in ArcGIS City Engine 2018 (Esri, CA, USA). The three virtual urban environments included low-rise buildings with heights between 5 m and 25 m, streets, trees, and open spaces. The cities were flat without any slopes, hills, mountains, or any global landmarks visible in the distance. The virtual environments were lit using sunlight without showing the sun, clouds, or other weather features. Figure 3.4 depicts the bird's-eye views and the first-person perspectives of the three virtual environments.

3.4.2 Virtual reality lab

The experiment was conducted in the GIVA CAVE (i.e., Cave Automatic Virtual Environment) Lab[2] located in the Department of Geography at the University of Zürich. The display of the three virtual cities was rendered in the three-sided CAVE, with the three screens in the front, to the left, and the right side of the participants, respectively (see Figure 3.5 a). The stereoscopic vision was simulated using the frame sequential projection with 1280 pixel × 800 pixel resolution at 120 Hz frequency (see Figure 3.5 b). To simulate the viewpoint-adapted stereoscopic image, participants wore a pair of 3D glasses that continuously tracked their head positions and orientations. The experimental tasks were programmed in C# and

[2] More information about the setup of the GIVA CAVE Labe can be found on the GIVA website: https://www.geo.uzh.ch/en/units/giva/services/cave-automatic-virtual-environment.html

rendered in Unity 3D 2018.4 LTS (Unity Technologies; San Francisco, CA, USA) and MiddleVR for Unity 1.0 (Truchtersheim, FR).

Figure 3.4 Left panel depicts bird's-eye views of the three virtual cities. To note, the bird's-eye view of the city was not presented to participants. Right panel depicts first-person perspectives in the three virtual environments during navigation.

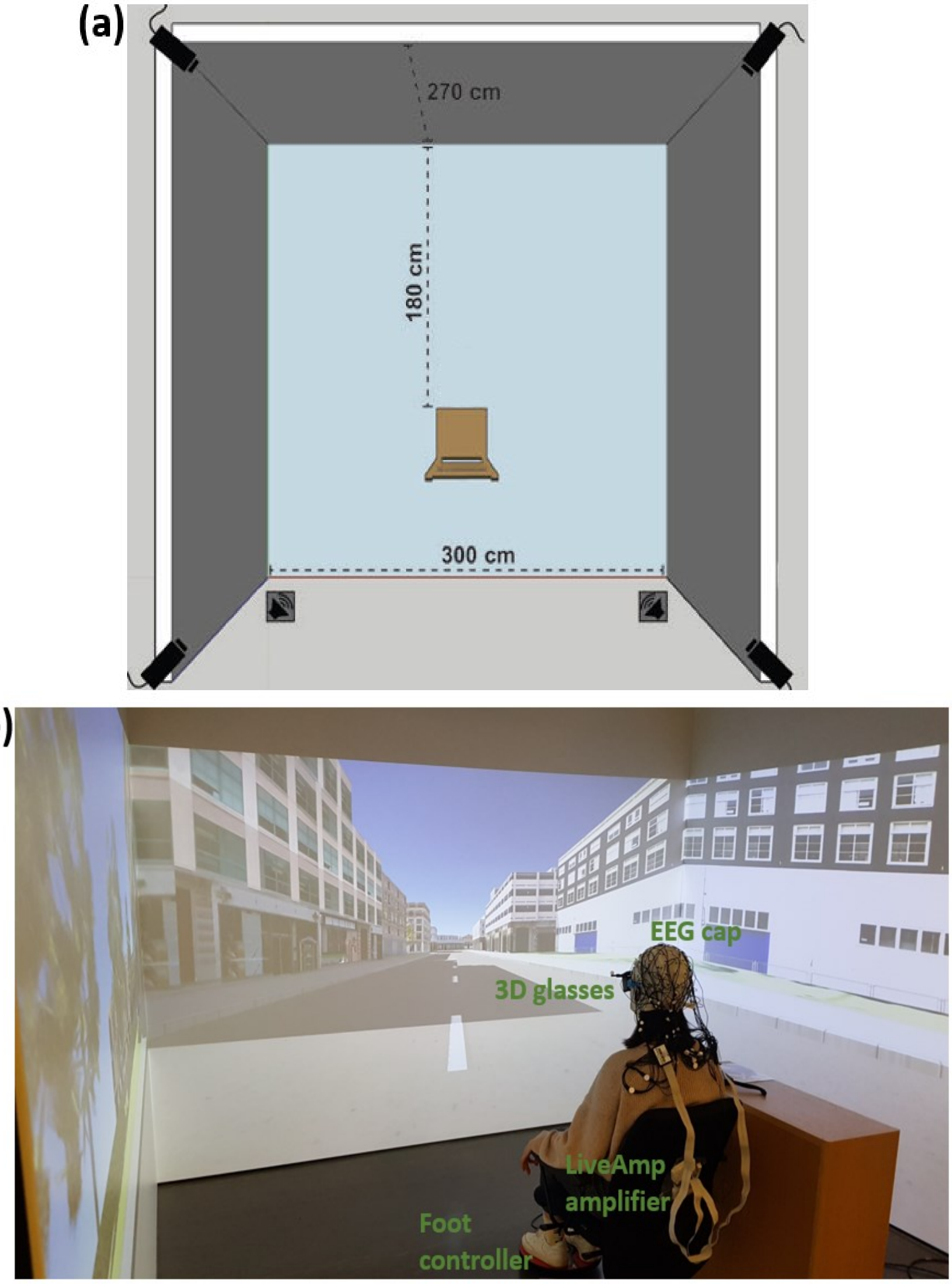
(a)
(b)


Figure 3.5 The top panel (a) illustrates the CAVE setup including the three-side walls and participants' sitting positions. The bottom panel (b) shows a participant wearing stereoscopic 3D glasses and placing her feet on a foot-operated controller to navigate through the virtual environment. The top panel (a) is adapted from Credé et al. (2019). The bottom panel (b) is adapted from Cheng et al. (2022).

Participants' movement through the virtual cities was connected to a foot-operated controller (3D Rudder, Aix-en-Provence, FR; www.3drudder.com). Participants titled the controller with their feet towards the front or back to simulate forward and backward movement in the virtual cities, respectively (see Figure 3.6 a, b). Tilting the controller left or right resulted in left or right rotation, respectively (see Figure 3.6 c, d). A previous study reported that using an external foot controller in a virtual navigation experiment could reduce participants' simulation sickness during the task (Credé et al., 2019). The moving speed was set at 3.8 m/s to minimize simulation sickness in the designed virtual environments, based on the individual's self-report during the pilot phase.

Figure 3.6 Top panel: the participant is titling the foot-operated controller with their feet to a) move forward and b) backward through the virtual city, respectively. Bottom panel: the participant is tilting the foot controller with their feet to c) the left and d) to the right to turn their heading direction in the urban virtual city towards the left and right, respectively. The figure is adapted from Cheng et al. (2023).

3.5. Measurements

This section deals with the behavioral tests and EEG techniques adopted to measure the dependent variables—spatial learning performance and brain activity (cognitive load and visuospatial encoding), respectively. Additionally, the measurement of individuals' spatial abilities is presented as a control variable in the experiment.

3.5.1 Spatial learning tests

A landmark recognition test, a route direction test, and a judgment of relative directions (JRD) test were utilized to assess participants' landmark, route, and survey knowledge, respectively. These three types of spatial knowledge are discussed in Section 2.1.2. Participants responded to the three tests using an electronic responding and pointing device, showed in Figure 3.7, also known as the wand (WorldViz Inc, USA).

Landmark recognition test

The landmark recognition test involved seven landmarks that were seen along the route (i.e., starting building, destination building, and the five buildings at the traversed intersections) and seven buildings that were selected from the same environment but not seen along the route, following prior related research (Huang et al., 2012; Kim & Bock, 2021; Stites et al., 2020; Wunderlich & Gramann, 2021). The seven landmarks from the route and seven buildings off the route in the landmark recognition test were identical in the three landmark conditions for each city. Participants were asked whether they had seen the landmarks along the route and pressed a button on the wand to respond "yes" or "no" (see Figure 3.7 a).

Route direction test

To assess participants' route direction memory, participants were additionally asked about the subsequent direction they took, in reference to the landmark for which they answered "yes" in the landmark recognition test. Participants used the wand to choose between "left", "right", "straight", and "destination" (see Figure 3.7 b), indicating that they had turned left, right, gone straight, and stopped at the goal, respectively. The paradigm of the landmark recognition and route direction tests was adjusted from the spatial knowledge tests used in prior navigation research (Huang et al., 2012; Wunderlich & Gramann, 2020, 2021).

JRDs

To access participants' acquired (metric) survey knowledge, we employed JRDs—a well-established test to measure navigators' knowledge of relative spatial directions between landmarks (Huffman & Ekstrom, 2018). One JRD trial involved three landmark locations of the seven landmarks along the route. Participants were asked to imagine standing at a first landmark while facing a second landmark and to point to a third landmark. For each JRD, participants used the wand to point to the estimated direction of the third landmark and confirmed their decision by pressing a button (see Figure 3.7 c). For each navigation trial, participants completed in total 14 JRDs, which were pseudo-randomly chosen out of all 35 possible JRD trials. The seven landmarks along the route appeared six times among the 14 JRD trials.

Figure 3.7 The three panels show how participants responded to the spatial learning tests using a 3D responding and pointing device after each navigation trial. The three panels depict (a) the landmark recognition test, (b) the route direction test, and (c) the JR JRD test, respectively. Figure 3.6 is adapted from Cheng et al. (2022).

3.5.2 EEG data collection

Participants' brain activity was continuously recorded using a 64-channel EEG device with active electrodes (LiveAmp, Brain Products GmbH, Gilching, DE). Electrodes were placed according to the international, extended 10% system (Oostenveld & Oostendorp, 2002). The nomenclature and position of the electrodes are discussed in Section 2.5.

All electrodes were referenced to FCz with a ground electrode at Fpz. The impedance of the electrodes was brought down below 10 kOhm to ensure the EEG data quality. The EEG data were collected at a 500 Hz sampling rate. The raw EEG signal was streamed wirelessly between the LiveAmp amplifier and Unity using a BlueTooth adapter (UBT21). The EEG signal and all trigger markers were synchronized through Windows Operating System's interprocess communication (I.P.C.).

3.5.3 Spatial abilities—control variables

A large body of literature has found that spatial abilities influence spatial learning performance (e.g., Burte & Montello, 2017; Weisberg & Newcombe, 2018). Therefore, I assessed individuals' spatial abilities and used them as a control variable for spatial learning.

Participants' spatial abilities were assessed by the previously validated Santa Barbara Sense of Direction Scale (SBSOD; Hegarty et al., 2002) and Perspective-Taking/Spatial-Orientation Test (PT/SOT; Hegarty & Waller, 2004). The SBSOD measures self-reported spatial and navigational abilities, preferences, and experiences (Hegarty et al., 2002). The questionnaire was presented to participants either in English (Hegarty et al., 2002) or in German (Münzer & Hölscher, 2011), based on their preferences. The PT/SOT uses a two-dimensional array of three objects where participants imagined themselves standing at one object in the array while facing another object with a particular direction within the array. The participants' task was to indicate the direction of the third object (Hegarty & Waller, 2004). To assess visuospatial working memory (VSWM) capacity, I administrated a computer-based Corsi block-tapping task (CBTT; Corsi1972, Brunetti2014). Nine squares were shown on the computer screen. A series of 3–9 squares were highlighted in a predefined sequence. Subsequently, participants had to click on the squares that were highlighted in the same sequence (Orsini et al., 1987). Each sequence length was repeated five times in a randomized order.

3.6 Power analysis and participants

To determine the number of test participants, a power analysis was conducted for a linear mixed-effect model (for more details of linear mixed-effect models, see Section 4.4), prior to conducting the experiment. I assumed a small-to-medium effect size (d = 0.3-0.5) for the within-participant conditions with 14 JRD trials each. The outcome of the power analysis suggested recruiting 50 participants to achieve a statistical power of 73% for a small effect and 89% for a medium effect, respectively.

49 participants (29 females) with ages ranging from 18 to 35 years (M = 25.6 years, SD = 4.09) were recruited and completed the experiment. The participants were recruited from the mailing lists of the Department of Geography and the Department of Psychology, University of Zürich. One participant's data were excluded due to self-reported illness during the experiment. All participants were financially compensated for their participation with 30 CHF. The study design and procedure were approved by the University of Zurich Ethics Board. All the procedures conducted in this study were also in accordance with the ethical standards of the Swiss Psychological Society and the American Psychological Association.

3.7 Procedure

The experiment was conducted in German or English based on participants' language preferences. On the day of the experiment, participants were first asked to read and sign the information sheet and the consent form. After that, they were introduced to the procedure of the experiment, as illustrated in Figure 3.8. Subsequently, participants completed the PT/SOT and SBSOD on a desktop computer in CAVE. Then participants were fitted with an EEG cap. Next, participants adjourned to the chair in front of the center of the CAVE screen and were given the instructions for the navigation task in VR. Following the experimenter's instructions, participants practiced walking with the foot-operated controller, using the mobile map in a training virtual city, and answering the spatial learning tests with the wand in CAVE. After the training session, participants proceeded to the main experiment if they had no further questions.

The main experiment consisted of three blocks and a two-minute break between the blocks. The participants completed all three experimental blocks. Each block included a map-assisted navigation task and three spatial knowledge tests. During the navigation portion, participants were instructed to follow the given route highlighted on the map as quickly as possible to a specific destination and to learn the landmarks along the route that were displayed on the map. Participants were also told that some landmarks at the intersections that were not visualized on the map would be tested after navigation. When participants deviated from the route, a message in the virtual environment appeared asking them to return to the route. Participants finished the navigation task when they arrived at the destination. After that, the experiment proceeded automatically to the spatial learning tests that assessed participants' landmark knowledge, route knowledge, and survey knowledge in a sequence. After the main experiment, participants completed the CBTT on a desktop computer in the same room. After the CBTT, the EEG cap was removed from the participant's head, and the participants received a debriefing about the study from the experimenter.

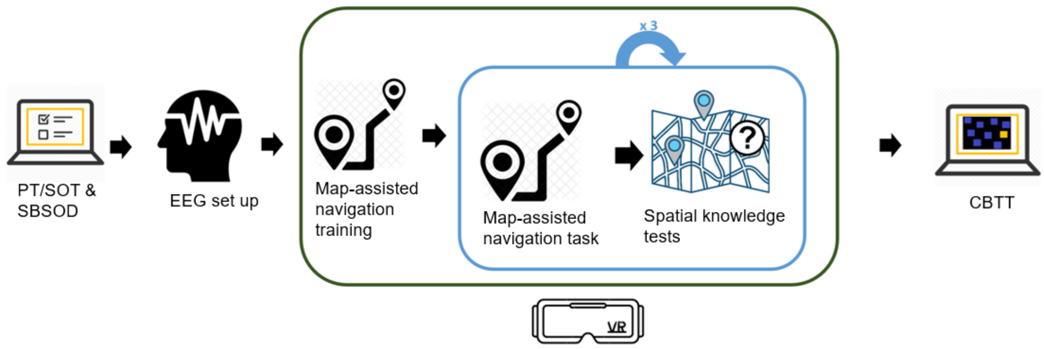


Figure 3.8 A flow chart illustrates the procedure of the experiment: the tasks (i.e., spatial abilities tests and questionnaire, navigation training, navigation task, and spatial knowledge test,), the sequence of the tasks, and the employed apparatus (i.e., a desk computer, EEG, and VR) during the experiment.

Chapter 4: Analyses

This chapter presents the methods adopted to analyze the acquired data of participants' spatial learning performance measured by three spatial learning tests and their brain activity measured by EEG, followed by the analyses of individuals' spatial abilities and VSWM capacity.

4.1 Spatial learning performance

To gain an understanding of how participants' spatial learning performance was influenced by the number of depicted landmarks (RQ1, H1), I analyzed their landmark recognition performance, route direction memory, and JRD errors after navigation, as discussed in the following sections.

4.1.1 Landmark recognition

Participants' landmark recognition data was acquired using the landmark recognition test, described in Section 3.5.1: Landmark recognition test. Signal detection theory (SDT; Parks, 1966) was employed to analyze participants' landmark recognition performance. The landmarks from the route were considered "signals" while buildings not seen along the route were conceptualized as "noise only" (Parks, 1966). If participants answered "yes" to an on-route landmark or off-route building, these decisions are marked as hits or false alarms, respectively (Table 4.1). D-prime (d') reflects the distance between the distributions of signal and of signal + noise and corresponds to the Z value of the hit rate minus that of the false-alarm rate (i.e., d' = $Z_H - Z_{FA}$) via *z-transformation*[3]. A d' of 3 is close to perfect performance; a d' of 0 corresponds to chance ("guessing") performance. Adjustments for false-alarm rates of zero or hit rates of one (i.e., P = 0, or P = 1) were made following the recommendations by Hautus (1995). After the adjustment, the effective limit of d' is 4.65. D' indicates participants' recognition discriminability; thus, higher d' scores indicate better discriminability in landmark recognition.

Table 4.1 Four outcomes of signal detection calculation. If a person detected the present signal (i.e., on-route landmarks) or absent noise (i.e., off-route buildings), these outcomes are called hits or false alarms, respectively. If the person rejected the present signal and absent noise, these decisions are marked as misses or correct rejections, respectively.

Stimulus / Response	Signal: On-route landmarks	Noise: Off-route buildings
"Yes"	Hit	False Alarm
"No"	Miss	Correct Rejection

4.1.2 Route direction memory

Participants' route direction choices were collected by the route direction test, described in Section 3.5.1: Route direction test. Responses for the landmarks that were on the route in the landmark recognition test were used for the route direction memory analysis (Kim & Bock, 2021). Responses for the buildings that were off the route in the landmark recognition test were discarded. To calculate the participant's route direction memory score, landmarks from the route that were not recognized were given a score of 0 on the route direction test. Responses for landmarks from the route that were recognized were scored as 1 for a correct direction response and 0 for an incorrect direction choice, respectively. Overall

[3] *"A range of values is cast as a normal distribution, with standard deviations around the mean. The mean value is set to 0, and the range of most values is about 3 standard deviations above and below the mean. So, each value is some number of SD units above or below the mean. This transform is valuable in allowing comparison of measures with different ranges of absolute values, and in taking into account the inherent variability of different measures."* (Pat Keating (2004))

performance on the route direction test was calculated as the percentage of correctly answered trials over the total number of assessed landmarks (seven).

4.1.3 JRD errors

Participants' JRD responses were collected using the JRD test, discussed in Section 3.5.1: JRDs. As depicted in the following Figure 4.1, the JRD error was defined as the absolute angular difference between the estimated direction (β) and the actual direction (α) of a target landmark relative to a reference landmark. These angular errors could vary between 0° (very accurate) and 180° (very inaccurate).

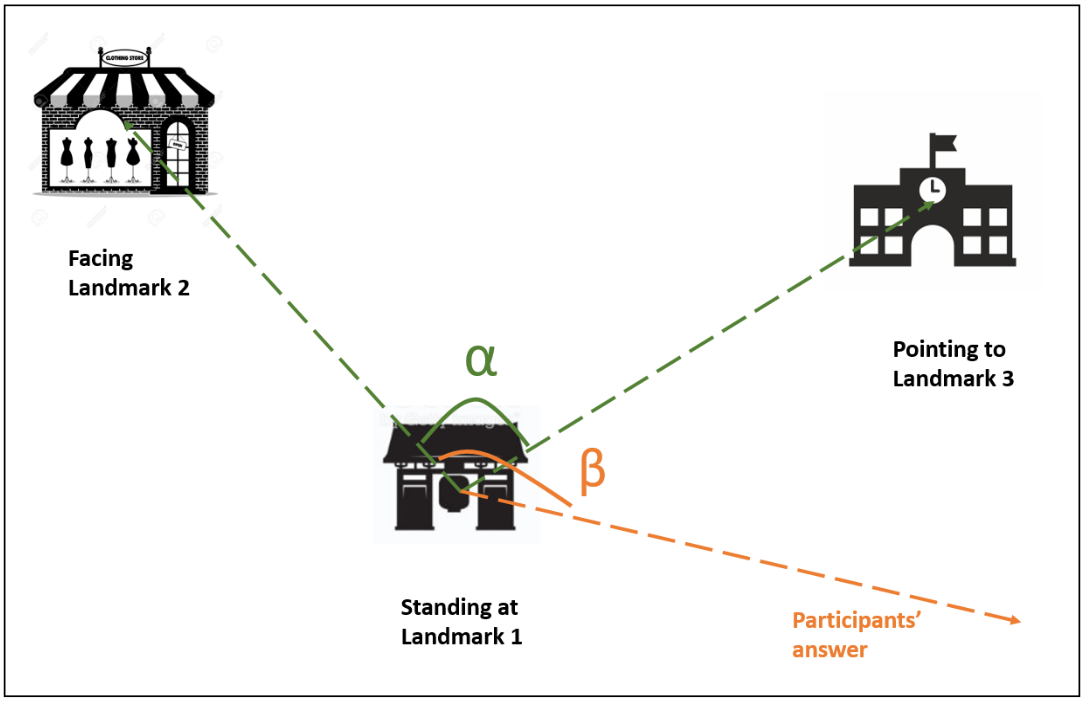


Figure 4.1 An illustration of the JRD error calculation. Participants are asked to point to Landmark 3 while imagining themselves standing at Landmark 1 and facing Landmark 2. The actual direction and responded direction are represented by α and β respectively. The JRD error equals the absolute difference between α and β: JRD error = $|\beta - \alpha|$.

The following sections deal with EEG data preprocessing and EEG data analyses to examine the hypotheses on the effects of the number of depicted landmarks on brain activity during map consultation (RQ2, H2) and during active locomotion (RQ3, H3). The EEG data were obtained following the EEG data collection described in Section 3.5.2. The obtained raw EEG recording is a mixture of genuine brain signals and noise, including eye movements, body movements, and channel noise. Thus, preprocessing EEG data is a crucial step to separate brain signals and noises before running the analysis on brain activity.

4.2 EEG data preprocessing

The raw EEG data was preprocessed and cleaned using the BeMoBIL pipeline (Klug et al., 2022) in the MATLAB version R2021a (Mathworks Inc., Natick, Massachusetts, USA) and in the toolbox EEGLAB 2021 (Delorme & Makeig, 2004). The BeMoBIL pipeline is designed to automatically preprocess EEG data and to ensure full replicability of all preprocessing steps. It also improves signal-to-noise ratios in mobile EEG datasets, which is crucial for optimizing independent component analysis (ICA, Makeig et al., 1995) to separate brain signals from noise in the EEG data. Below, I describe each preprocessing step, the employed toolboxes and functions in the toolboxes for each step, and the corresponding outcomes of each step in the BeMoBIL pipeline.

Before submitting the raw EEG data into the BeMoBIL pipeline, the non-experimental segments (e.g., breaks between the experimental blocks) were removed from the EEG datasets. Then, the raw EEG data was then downsampled to 250 Hz to reduce the EEG data size and speed up the preprocessing procedure. Next, the *ZapLine Plu*s function was applied to remove spectral peaks at 50 Hz, in correspondence to the power line frequency (Klug & Kloosterman, 2022). The noisy channels were identified using the automated rejection function *clean_artifacts* with ten iterations. The noisy or dead channels that were detected more than four times out of the ten iterations were removed, based on their correlations with other channels (threshold = 0.85), maximal flat line periods (threshold = 3 seconds), and detected fraction (threshold = 0.4). The missing channels (M =3.7, SD = 2.5) were interpolated using a spherical spline function from EEGLAB. The data was then re-referenced to the average reference across the whole set of channels.

Subsequently, ICA was performed using an adaptive mixture independent component analysis (AMICA) algorithm (Palmer et al., 2011), setting the parameter values according to the default recommendations from Klug and Gramann (2021). The AMICA decomposition employs a log-likelihood algorithm to remove the data samples that are not in accordance with the estimates of the model fit. Three standard deviations were used as removal criterion and five iterations were applied in AMICA cleaning. Apart from the AMICA-inherent time-domain cleaning, automatic time-domain rejections and high-pass filtering with a 2-Hz low-cutoff filter were conducted before AMICA, to optimize the ICA decomposition that condenses the data into a series of statistically, maximally independent components (ICs).

For each resultant IC, an equivalent current dipole (ECD) model was computed using the DIPFIT plugin from EEGLAB (Oostenveld & Oostendorp, 2002). The computed information including spatial filters and dipole models resulting from AMICA was copied back to the preprocessed but unfiltered EEG data (i.e., no cleaning in the time domain), considering that EEG measures (e.g., ERPs) in the later analyses may require filtering with a lower cutoff on the EEG datasets (Klug et al., 2022; Klug & Gramann, 2021).

After the aforementioned preprocessing steps in the BEMOBIL pipeline, a 0.5–30 Hz pass filter was applied to suppress slow drifts and high-frequency activity in the EEG signal. One participant was excluded from further EEG analyses because of severe artifacts in their EEG data. Lastly, 47 participants' EEG data were submitted for further EEG analyses to examine event-based brain activity during map viewing and blink-based brain activity during locomotion respectively, which is discussed in the following sections.

4.3 Brain activity during map consultation

To analyze the brain signals that reflect cognitive load and visuospatial encoding during map consultation, I first extracted the EEG data in relation to the map-viewing phase from the continuous EEG recordings. The step of map-event extraction resulted in 17 map-onset EEG epochs. Second, I selected the relevant EEG electrodes that represent the brain regions of interest (ROIs) for cognitive load and visuospatial encoding. Next, I submitted the 17 map-onset epochs with the selected electrode clusters of interest into ERP analysis and PSA. These two EEG analysis techniques returned ERP components and frequency band power respectively, which are used as neural indicators of cognitive load and visuospatial encoding, as reviewed in Section 2.5. Detailed EEG analysis steps are presented in the following sections.

4.3.1 Map-event extraction

The map-event latencies marked on the continuous EEG recordings were corrected based on the latencies of the CAVE projector (33 ms) and EEG trigger (100 ms) due to the delays in wireless transmission. Then, 17 map-onset epochs were extracted from the continuous EEG data with a time window of 0–5 s with respect to map onset and with a pre-event baseline of -1 to 0 s. The spatial distribution of the 17 map-onset events along the route is discussed in Section 3.3.2: Mobile map assistance.

To clean the extracted epochs, an automatic epoch artifact detection and rejection was then performed using the function *pop_autorej* in EEGLAB. Epochs that fluctuated more than ±80 μV were excluded, following the recommendations from Duncan et al. (2009). In addition, a probability threshold of three in standard deviation was used for the detection of improbable data. A maximum of 10% of total trials were rejected per iteration (five iterations in total). On average, 4.19% of all trials (0.7 out of 17 epochs) were excluded based on these criteria.

Notably, the remaining map-onset events along each navigation route were averaged for further analyses in the ERPs and PSA in the frequency domain, to analyze the *general* effects of the number of landmarks on cognitive load and visuospatial encoding during map consultation.

4.3.2 Regions of interest

Prior neuroscientific research reports that maximal effects of cognitive load for theta band power are found at fronto-central leads and for alpha band power and P3 component are found at parietal-occipital leads (Dong et al., 2015; Scharinger et al., 2017; Wei & Zhou, 2020) as well as of visuospatial encoding for theta and alpha band power at occipital and parieto-occipital leads (Handy et al., 2001; Wei & Zhou, 2020). Thus, the following ROIs and channel clusters were chosen: fronto-central (electrodes: FC1, FCz, FC2), parieto-occipital (electrodes: PO3, POz, PO4), and occipital (electrodes: O1, Oz, O2) regions. The positions of the selected channel clusters are highlighted in Figure 4.2.

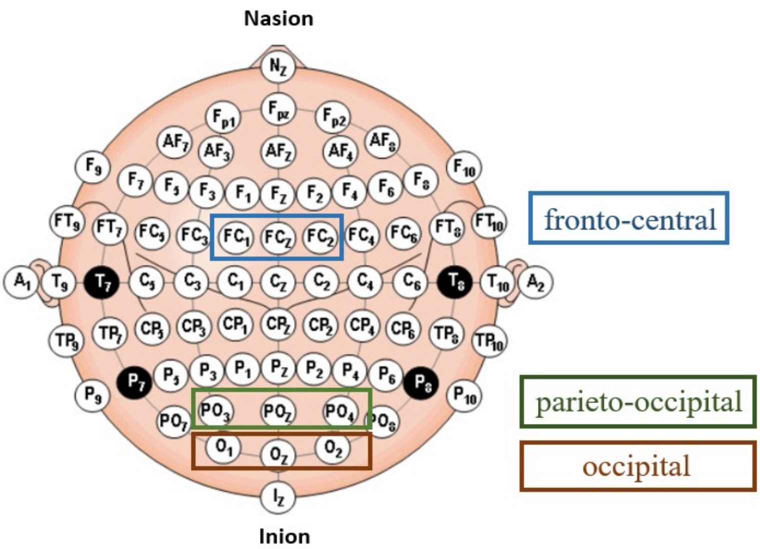


Figure 4.2 The electrodes highlighted in the color boxes represent the selected channel clusters of 17 map-onset epochs to examine cognitive load and visuospatial encoding. The top, middle, and bottom channel clusters represent fronto-central, parioto-occipital, and occipital leads, respectively. The figure is adapted from Tang et al. (2019), https://doi.org/10.31083/j.jin.2019.01.103.

Next, the 17 map-onset EEG epochs with the selected electrode clusters were submitted for the ERP analysis and power spectral analyses to examine cognitive load and visuospatial encoding during map consultation.

4.3.3 ERP analysis

The ERP analysis in this thesis followed the standard approach of obtaining ERPs introduced in Section 2.5.1. First, a pre-stimulus baseline from -200 to 0 ms was used to correct obtained single-trial EEG data epochs. Next, map-based EEG data epochs of each ROI were averaged across all trials and all participants for each landmark condition (i.e., three, five, and seven landmarks). This step resulted in the grand averaged ERP plots that serve to determine the time windows for the components of interest. The grand averaged ERP plots are depicted in Section 5.2.1. Subsequently, the time windows were selected for the components of P1 (80–150 ms) at occipital sites and P3 (450–700 ms) at the parietal-occipital region and were used for individual peak detection. Compared to the approach of averaging the amplitude across the selected time windows, individual peak detection is sensitive to the differences between conditions and participants (Wunderlich & Gramann, 2020). Peak amplitude was computed by taking the mean of the maximum peak value in the respective time windows and the neighboring +1 and -1 sample points (in total three data samples; equals 12 ms), following the method by Wunderlich and Gramann (2020).

4.3.4 Power spectral analysis

To compute power spectra in different frequency bands, an EEG function *spectopo* was employed. This function uses Matlab's *pwelch* function and results in power spectral density (PSD). For PSD estimation, a 2-s Hanning window that led to a frequency resolution of 0.5 Hz was used to capture spectral changes in the EEG data. Four frequency bands were set with the following frequency ranges: delta (1–3.9 Hz), theta (4–7.9 Hz), alpha (8–12.9 Hz), and beta (13–29.9 Hz). The absolute spectrum of each frequency band was calculated within the 0 to 5s epoch with stimulus onset. Then, the relative power indices for each frequency band were calculated as power in a given band relative to the entire bandwidth (i.e., 1–30 Hz). Using relative power indices reduces inter-individual deviation in power spectra

(Nishiyori et al., 2021; Y. Wang et al., 2015). The following formula (4.1) describes the procedure of the relative band power calculation:

relative theta power = [absolute theta power / absolute power of (theta + alpha + beta + delta)] 100* *(4.1)*

Baseline power in different frequency bands was calculated as relative power indices during the time before the navigation portion of the experiment started, that is, while participants were sitting on the chair and viewing a dark blue screen of the front CAVE wall. The baseline period started when participants put on the 3D stereo goggles and ended when the first virtual environment was fully loaded and presented on all walls of the CAVE. The baseline phase varied from 6 s to 20 s, depending on when participants felt ready to start the navigation task. Baseline epochs were extracted with a length of 1 s from this pre-navigation experiment phase. Each baseline epoch had a 200-ms overlap with the subsequent epoch, given that the overall pre-navigation baseline phase was short. This approach ensured that a sufficient number of baseline epochs were obtained to calculate relative power indices.

Subsequently, alpha ERD (negative values) and theta ERS (positive values) were calculated with respect to the pre-navigation baseline using the following formula (4.2), following the prior studies (Dong et al., 2015; Krause et al., 2000; Pfurtscheller & Lopes da Silva, 1999):

ERD or ERS = (relative power during map-event-relative power during baseline) / relative power during baseline *(4.2)*

The resultant P3 amplitude from the ERP analysis, the alpha ERD, and the theta ERS obtained from the PSA were submitted to the linear mixed-effect models for hypothesis testing (H2). The linear mixed-effect models are described in the subsequent Section 4.6.

4.4 Blink-related brain activity during locomotion

To examine cognitive load and early visual encoding during active locomotion, I adopted spontaneous eye blinks as EEG event markers and analyzed brain activity related to the detected eye blinks. First, I detected blinks on the preprocessed EEG data obtained from Section 4.2 and labeled these detected blinks as event markers on the EEG data. Second, I cleaned the EEG data based on classified brain components (source-based cleaning). Next, I submitted the cleaned EEG data to extract the bERP components. The bERP analysis in this thesis followed the protocol established by Wunderlich and Gramann (2020) and Wascher et al. (2014). The following sections present each analysis step in detail.

4.4.1 Eye blink detection

First, the map presentation events (5-s time windows) were removed from the preprocessed continuous EEG data. On the resultant EEG data, the independent component representing vertical eye movements was identified and filtered using a moving median approach with a window size of 20 sample points (i.e., 80 ms). The moving median approach preserves the steepness of eye movements and does not introduce any artificial signal changes into the data (Bulling et al., 2011). Next, blink peaks were detected in the vertical eye movement component using the *findpeaks* function in MATLAB with the following blink parameters: *minimal peak width* of five time points (20 ms) and *maximal peak width* of 65 time points (260 ms) to prevent potential high-amplitude artifacts or slow oscillations from being detected as a blink; *minimal peak distance* of 25 time points (100 ms) to avoid directly following blinks being included; *minimal peak height* was defined as peak heights ≥ 96 percentile; *minimal peak prominence* was defined as peak prominence ≥ 97 percentile. Event markers, labeled as *blinks*, were created and placed in the EEG data at time points of maximum blink deflections.

4.4.2 Source-based EEG data cleaning

The ICLabel algorithm (Pion-Tonachini et al., 2019) was used to classify the obtained ICs into seven classes (i.e., brain, muscle, eye, heart, line noise, channel noise, and other). Based on this classification, ICs that were classified as unlikely to represent brain activity were removed from the data; the removal criterion was set at a classification probability lower than 30% in the category brain, following the approach suggested by Wunderlich and Gramann (2020) for Mobile Brain/Body Imaging (MoBI) EEG data.

The conservative threshold of 30% was chosen to avoid excluding any potentially useful brain sources, based on the following considerations: first, as the *ICLabel* algorithm was mainly trained on stationary datasets and only very few MoBI datasets to classify ICs, the classification of movement-related activity stemming from the neck musculature and other such sources is usually not accurate. Furthermore, increasing the number of movement-related brain and non-brain sources can increase the likelihood of brain sources being mixed with other sources, while having only a limited number of channels and thus only limited degrees of freedom for the decomposition. This in turn can result in non-standard IC topographies and spectra. After the IC cleaning, the number of ICs per participant was reduced to on average 30.0 (*SD* = 4.1 ICs, *Min* = 20 ICs, *Max* = 40 ICs). The cleaned EEG data were then backprojected to the sensor level for further analyses in the bERPs and the exploratory PSA.

4.4.3 Blink-related ERP extraction and analysis

To extract bERPs, the Unfold toolbox (Ehinger & Dimigen, 2019) was used on blink events during the locomotion phase. The unfolding technique allows the separation of overlaying event-based brain activity (e.g., two blinks happening very close to each other) using a regression-based approach. This is useful for the current EEG data, considering that the blink rate is high during naturalistic navigation in an open-world virtual environment (Enders et al., 2021).

A design matrix was created with the blink events and 65 EEG channels. Information on each landmark condition (i.e., three, five, and seven landmarks) was entered into the regression formula y = 1 + cat(landmark). Continuous artifact detection and rejection were applied with an amplitude threshold set at ± 80 microVolts (μVs) during unfolding, to remove the noisy segments from the continuous EEG datasets. Next, the design matrix was time-expanded based on the time limits of -500 to 2000 ms with reference to blink events. Then, a general linear model was fitted to solve the intercept and beta values with a baseline correction at -500 to -200 ms prior to the blink event.

Subsequently, bERPs were recovered and modeled from the unfolded intercept and beta values using matrix multiplication (Ehinger & Dimigen, 2019) for the selected electrodes of interest (Fz, FCz, Pz, POz, and Oz), based on studies by Wascher et al. (2014, 2016). The time window of each component of interest was selected based on visual inspection of the grand averaged bERP plots (see Section 5.3.1). The N1 amplitude was extracted 110–150 ms after blink maximum and averaged across the occipital (Oz). The N2 amplitude was extracted 250–390 ms after blink maximum and averaged across fronto-central leads (Fz and FCz). The P3 was extracted 250–340 ms after blink maximum and averaged across parieto-occipital leads (Pz, POz, and Oz).

Individual peak detection was used to capture the peak amplitude of each component in the selected time window by taking the average of the maximum peak value with the neighboring +3 and -3 sample points around the detected peaks (i.e., seven data samples in total; 24 ms in total; F. Sugimoto et al., 2022; Takeda et al., 2014).

4.4.4 Blink-related power spectral analysis–exploratory analysis

The PSA in reference to blinks was performed as an *exploratory analysis* to provide converging evidence for cognitive load during locomotion. First, the segments of -500 to +2000 ms were extracted with respect to blink events as the epochs for power calculation in the frequency domain. Then, blink-related power calculation replicated the approach of map-based power analysis, described in Section 4.3.4. The fronto-central theta ERS and parieto-occipital alpha ERD during active locomotion through the environment were computed relative to the pre-navigation baseline phase using the following formula (4.3):

$$ERS \text{ or } ERD = (\text{relative power during active locomotion} - \text{relative power during baseline}) / \text{relative power during baseline} \quad (4.3)$$

Subsequently, the resultant bERP components (N1, N2, P3), the alpha ERD and the theta ERS were entered into the linear mixed-effect models for hypothesis testing (H3).

4.5 Spatial ability analysis

The data on individuals' spatial abilities were acquired by self-reported SBSOD questionnaire, PT/SOT, and CBTT, as presented in Section 3.5.3. The SBSOD scores were calculated as the average scores across the 15 items. The scores range from 1 to 7, where higher scores indicate a better sense of orientation. The PT/SOT scores were calculated as the average absolute angular error in degrees over all 12 trials. Any trial that was not answered during the time period was scored as a 90-degree error (i.e., chance performance). The VSWM span was calculated as the highest number of items where participants answered three out of the total five trials correctly in the CBTT (Orsini et al., 1987; Trojano et al., 1994).

The obtained SBSOD scores, the PT/SOT scores, and VSWM spans were entered into the linear mixed-effect models in relation to spatial learning performance, as a control variable.

4.6 Statistical analysis: linear mixed-effect models

I utilized linear-mixed effect models to statistically examine the effects of the landmark conditions (3 versus 5 versus 7 landmarks) on spatial learning, cognitive load, and visuospatial encoding during navigation. The linear mixed-effect modeling approach, also known as multilevel linear regression modeling, is a generalized form of regression analysis that enables hypothesis testing for nested study designs, such as within-participants designs and multiple trials within participants (Gelman, 2006). This means that the model estimates the effects of a by-participant or by-item individual predictor and its group-level mean separately (Gelman, 2006) and produces more statistical power for the statistical outcomes of the data collected using a nested study design. Moreover, the linear mixed-effect modeling approach ignores missing values in predictors without requiring imputations or discarding the participant (Gabrio et al., 2022). This allowed me to perform within-participant analyses for the behavioral and EEG outcomes and to include two participants with incomplete EEG data in the analyses.

I entered the spatial learning outcomes (i.e., d', route direction choices, JRD errors) and EEG measure outcomes (i.e., P3 amplitude, P1 amplitude, theta ERS, alpha ERD) in R version 4.0. I built a linear mixed-effect model for each learning or EEG outcome using the *lmer4* package (Bates et al., 2011). Next, I ran the built linear mixed-effect models using *lmer4*, with the α level set at .05 for all analyses.

In this thesis, I adopted the mixed-effects regression as a hypothesis-driven confirmatory approach. Based on the recommendations by (Barr et al., 2013) on multilevel models for confirmatory hypothesis testing, I first established the maximal random-effects structure by including by-participant intercepts and slopes, based on the within-participant study design. I then simplified the maximal random-effects structure by first removing random slopes and then random intercepts until the resultant model converged. The first model that converged included by-participant intercepts in the random-effects structure for the spatial learning outcomes and EEG measures.

For the spatial learning outcomes, I added spatial ability scores (i.e., the VSWM spans, SBSOD scores, and PT/SOT scores) in the mixed-effect models to control for the individual's spatial abilities.

The following equation (4.4) described the linear mixed-effect model that controls individuals' SBSOD scores:

$$Dprime_{pi} = \beta_0 + \beta_1 * Condition_i + \beta_2 * SBSOD_p + P_{0p} + e_{pi} \qquad (4.4)$$

The following equation (4.5) described the resultant linear mixed-effect model for EEG measures:

$$Theta\ ERS_{pi} = \beta_0 + \beta_1 * Condition_i + P_{0p} + e_{pi} \qquad (4.5)$$

where $Theta\ ERS_{pi}$, for participant p and item i, is associated with a reference level via fixed-effect β_0 (the intercept), a landmark condition effect via fixed-effect β_1 (the slope), the deviation from β_0 for participant p, and the observation-level error e_{pi}. In this model, parameters β_0 and β_1 represent fixed effects, and the parameter P_{0p} represents random effects.

Chapter 5: Results

This chapter concerns the statistical results returned by the linear mixed-effect models, examining the effects of the number of landmarks on spatial learning performance (i.e., landmark recognition, route direction memory, and JRDs) and brain activity (i.e., cognitive load and visuospatial encoding). I first report participants' overall time spent navigating the virtual urban environment.

The navigation time in each city was calculated as the time taken to navigate from the starting location to the destination in the virtual environment. Participants spent on average 8.11 minutes (*SD* = 1.63 min) navigating in each virtual city. The linear mixed-effect models revealed no significant difference in navigation time between the three landmark conditions (*ps*[4] > .507). This suggests that modifying the number of landmarks on a mobile map did not influence participants' navigation time in virtual cities.

5.1 Effects of the number of landmarks on spatial learning

The 48 participants produced 144 d's, 144 route direction choices, and 1981 JRD responses, of which 35 JRD responses were lost due to random technical reasons in Unity. The mean of d' was 1.85 (*SD*= 0.76), the mean percentage of correct route direction choice was 62% (*SD* = 0.26), and the mean of the absolute JRD error was 72.64° (*SD* = 48.06°).

5.2.1 Landmark recognition

The linear mixed-effect models reported a significant effect of the number of landmarks on landmark recognition. Participants' recognition discriminability d' increased by 0.51 points when the number of landmarks displayed on a mobile map increased from three

[4] ps denotes multiple p values.

to five (β = 0.51, *95% CI* = [0.30, 0.72], p < .001). No further improvement in landmark recognition discriminability was observed from five landmarks to seven landmarks (β = -0.11, *95% CI* = [-0.32, 0.10], p = .31).

5.2.2 Route direction memory

The linear mixed-effect models also reported a significant effect of the number of landmarks on route direction memory, which demonstrated a similar pattern to the effect on landmark recognition. Route direction memory significantly improved by 12% on average when the number of landmarks increased from three to five (β = 0.12, *95% CI* = [0.57, 0.67], p < .001), and did not further improve from five to seven (β = -0.02, *95% CI* = [-0.09, 0.06], p = .71).

5.2.3 JRD response errors

For the JRD response errors, the linear mixed-effect models showed no significance between the three landmark conditions (5 vs 3: β = -1.09, *95% CIs* = [-6.22, 4.04], p = .68; 7 vs 5: β = 0.49, *95% CIs* = [-4.61, 5.58], p = .68).

5.2.4 Summary of spatial learning performance

In summary, landmark recognition and route direction memory increased when the number of landmarks increased from three to five, and there was no further improvement when the seven landmarks were shown. No difference in JRD performance was found between the three landmark conditions. The discussion of these findings is presented in Section 6.1.

Figure 5.1 below depicts the relationship between the number of landmarks displayed on a mobile map and spatial learning (i.e., landmark recognition, route direction memory, and

JRDs). Table 5.1 below provides a complete overview of the obtained coefficients of the linear mixed-effect models on spatial learning.

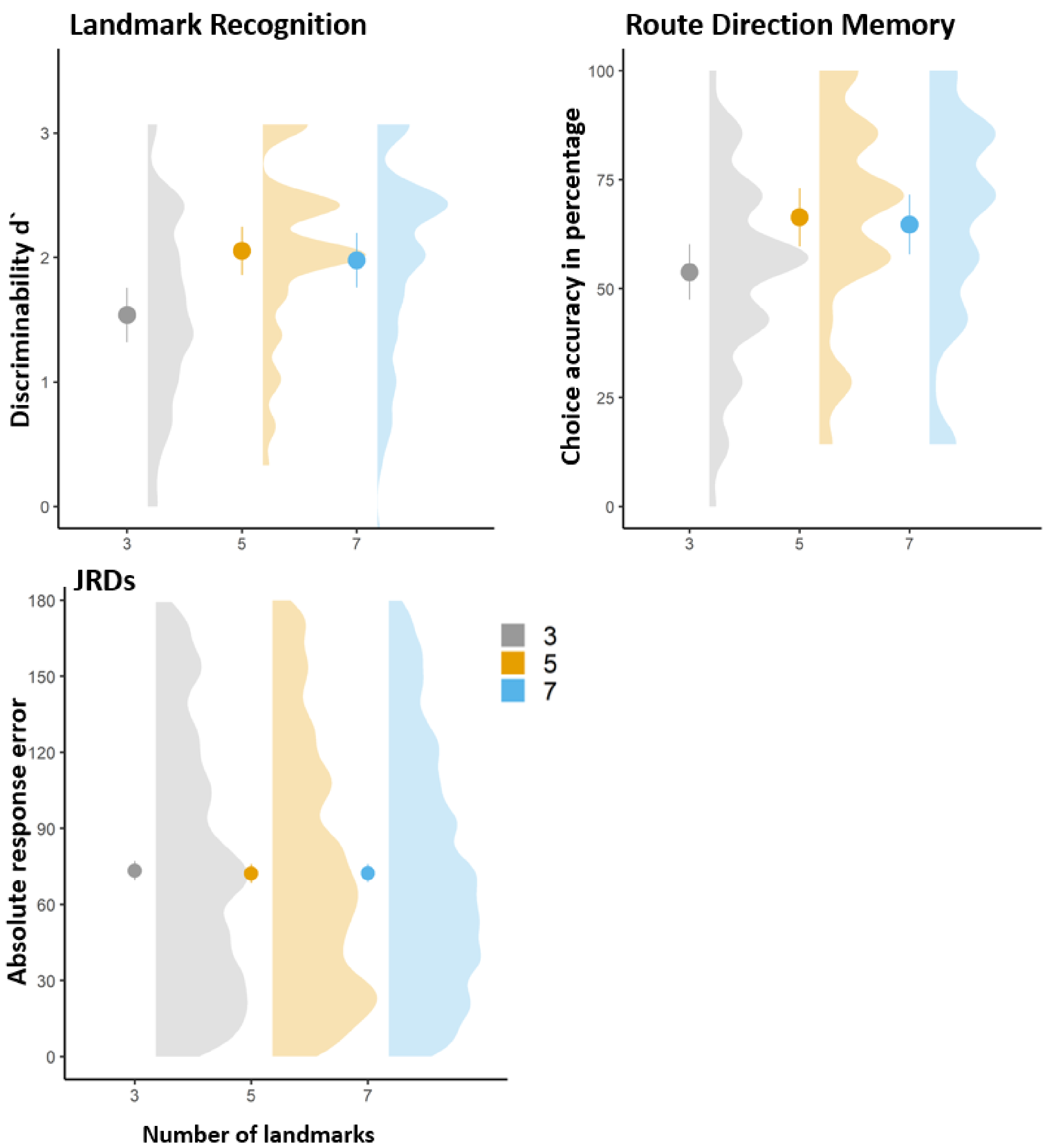


Figure 5.1 Landmark recognition and route direction memory improved when more than three landmarks were shown. No improvement was observed in JRD performance when more landmarks were shown. The means of d', choice accuracy, and absolute response error in each landmark condition are presented in the three plots with the error bars representing the 95% CI of the mean.

Table 5.1 Linear regression coefficients of spatial learning performance (i.e., landmark recognition, route direction memory, and JRDs) in the three landmark conditions.

Spatial learning test	LM condition contrast	β	95% CI	*p*
Landmark Recognition	5 vs 3	0.51	0.30 – 0.72	**<.001**
	7 vs 5	-0.11	-0.32 – 0.10	.31
Route Direction	5 vs 3	0.12	0.57 – 0.67	**<.001**
	7 vs 5	-0.02	-0.09 – 0.06	.71
JRDs	5 vs 3	-1.09	-6.22 – 4.04	.68
	7 vs 5	0.49	-4.61 – 5.58	.86

After having presented the spatial learning outcomes, the subsequent sections deal with the results of brain activity during map consultation and locomotion, respectively.

5.3 Effects of the number of landmarks on brain activity during map consultation

In this section, I first present the findings of cognitive load—a higher cognitive load would be indicated by a larger parieto-occipital P3 amplitude, fronto-central theta synchronization, and parieto-occipital alpha desynchronization. I then describe the results of visual and spatial encoding—a higher degree of visual and spatial encoding would be indicated by a greater occipital P1 amplitude along with posterior theta synchronization and alpha desynchronization. The P1 and P3 components resulted from ERP analysis; theta and alpha power resulted from PSA.

5.3.1 Cognitive load–P3

The linear mixed-effect models on ERPs revealed that P3 amplitude in the parieto-occipital region did not change when the number of landmarks increased from three to five (5 vs. 3: $\beta = 0.04$, *95% CI* = [-0.92, 1.00], $p = .936$). The P3 amplitude increased by 139% on average from the five-landmark to seven-landmark condition (7 vs. 5: β = 1.39, *95% CI* = [0.44, 2.35], p = .004). Figure 5.2 plots the group-mean amplitude of the parieto-occipital ERP signal and the means of the detected P3 peak amplitude for each landmark condition in the left and right panels, respectively.

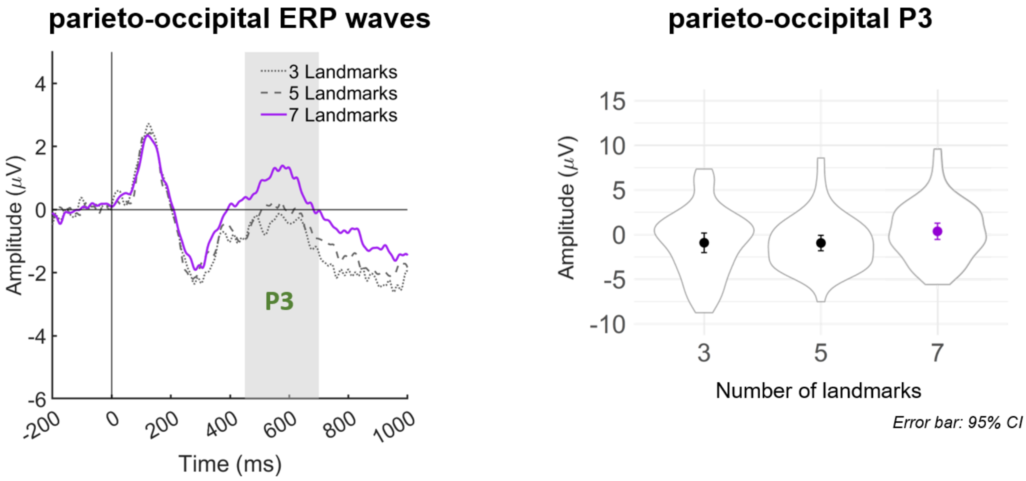


Figure 5.2 The left panel depicts the grand averaged amplitudes of ERPs for each landmark condition at parieto-occipital leads (PO3, POz, PO4). The ERP plots served as the basis for selecting the time windows for individual peak detection—vertical bars shaded in gray represent the time window in which maxima of the P3 (450–700 ms) was extracted for each single-trial epoch. The right panel shows the violin plots that display the distribution (i.e., the violin shape) of the detected peak amplitudes together with a mean (i.e., the dot in the middle of the violin shape) and ± 1.96 standard error—95% CI (i.e., the error bar) in each landmark condition for parieto-occipital P3 component. Significant differences at $p < .05$ between the landmark conditions were highlighted in purple in the line plot in the left panel and means in the right panel.

5.3.2 Cognitive load–theta and alpha

The linear mixed-effect models on the relative theta ERS at fronto-central leads demonstrated a similar pattern as the previously reported P3 component. No significant difference was found in the relative theta ERS between the three-landmark and five-landmark conditions (5 vs. 3: β = -0.03, *95% CI* = [-0.09, 0.04], p = .391). However, the relative theta ERS significantly increased when the number of landmarks increased from five to seven (7 vs. 5: β = 0.10, *95% CI* = [0.04, 0.16], p = .002).

No statistically significant difference was observed in relative alpha ERD in the parieto-occipital region between the landmark conditions (5 vs. 3: β = -0.03, *95% CI* = [-0.09, 0.02], p = .220; 7 vs. 5: β = -0.01, *95% CI* = [-0.06, 0.05], p = .738). Figure 5.3 below depicts the averaged relative theta ERS in the fronto-central region and relative alpha ERD in the parieto-occipital region across the three landmark conditions.

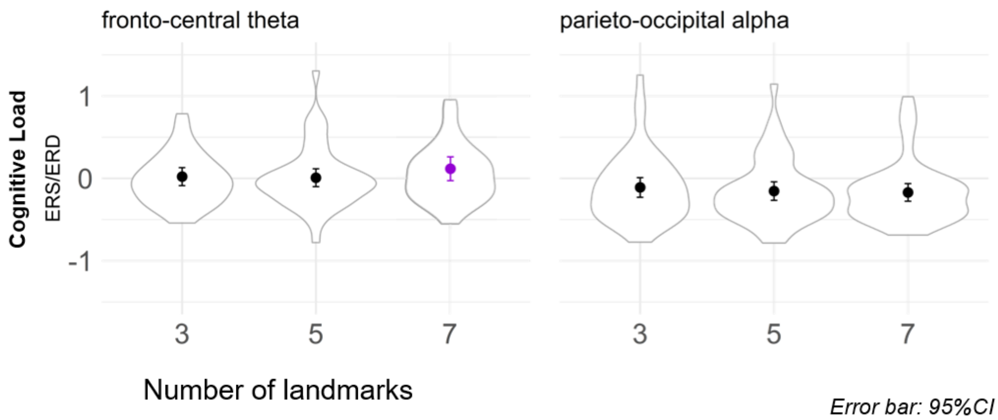


Figure 5.3 Violin plots of frontal-central relative theta ERS (the left panel) and parieto-occipital relative alpha ERD (the right panel) values of the map-event window (i.e., 0–5 s) indicate cognitive load changes. Dots in the middle of the violin shapes indicate the means of each distribution of ERS/ERD values (i.e., the violin shapes). ERS and ERD were corrected to a pre-experiment baseline. Error bars indicate ± 1.96 standard error (i.e., 95% CI) of the mean. The mean in the violin plot highlighted in purple indicated a significant difference at $p < .05$ between the landmark condition. Means depicted in the same color within the same violin plot represent no significant difference between the means at $p \geq .05$.

5.3.3 Early visual encoding–P1

No significant difference was observed in P1 amplitude in the occipital region and in the parietal-occipital region between the three conditions (5 vs. 3: β = 0.25, *95% CI* = [-0.38, 0.88], p = .439; 7 vs. 5: β = -0.47, *95% CI* = [-1.10, 0.16], p = .139). Figure 5.4 plots the group-mean amplitude of the occipital ERP signal and the means of the detected P1 peak amplitude for each landmark condition in the left and right panels, respectively.

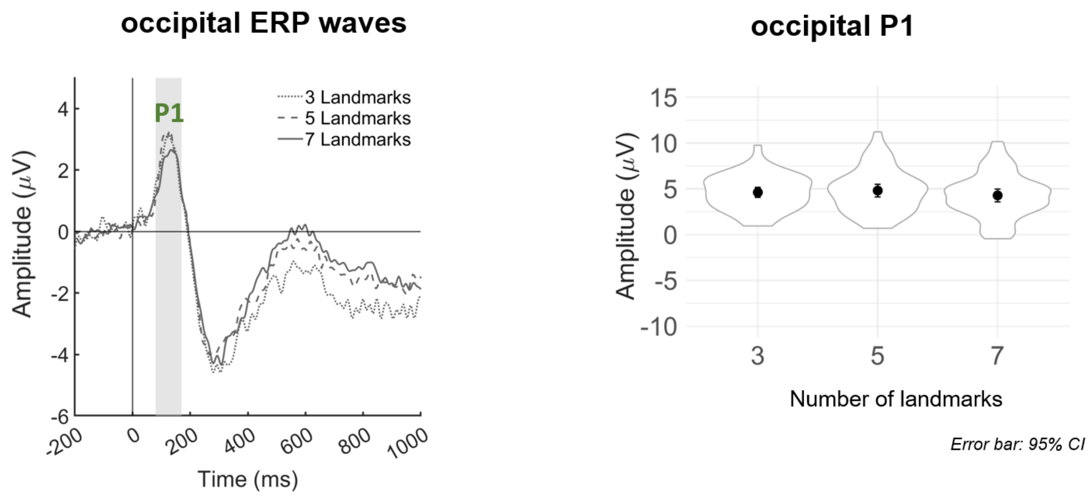


Figure 5.4 The left panel depicts the grand averaged amplitudes of the ERP waves for each landmark condition at occipital leads (O1, Oz, O2). The ERP plots served as the basis for selecting the time windows for individual peak detection—vertical bars shaded in gray represent the time window in which the maxima of the P1 (80–150 ms) was extracted for each single-trial epoch. The right panel shows the violin plots that display the distribution (i.e., the violin shape) of the detected peak amplitudes together with a mean (i.e., the dot in the middle of the violin shape) and ± 1.96 standard error—95% CI (i.e., the error bar) in each landmark condition for the occipital P1. No significance was observed between the three landmark conditions.

5.3.4 Visuospatial encoding–theta and alpha

Relative theta ERS in the parieto-occipital region significantly increased with increasing numbers of landmarks (5 vs. 3: $\beta = 0.06$, *95% CI* = [0.01, 0.11], $p = .027$; 7 vs. 5: $\beta = 0.09$, *95% CI* = [0.04, 0.14], $p = .001$). This pattern of relative theta ERS was also found in the occipital region (5 vs. 3: $\beta = 0.06$, *95% CI* = [0.01, 0.11], $p = .027$; 7 vs. 5: $\beta = 0.08$, *95% CI* = [0.02, 0.14], $p = .008$).

Relative alpha ERD in the occipital region increased when five landmarks were shown, compared to three landmarks (5 vs. 3: $\beta = -0.09$, *95% CI* = [-0.16, -0.03], $p = .006$). No significant difference was found between the five-landmark and seven-landmark conditions

(7 vs. 5: β = 0.02, *95% CI* = [-0.05, 0.09], p = .541). Figure 5.5 below depicts the averaged relative theta ERS and relative alpha ERD across the three landmark conditions.

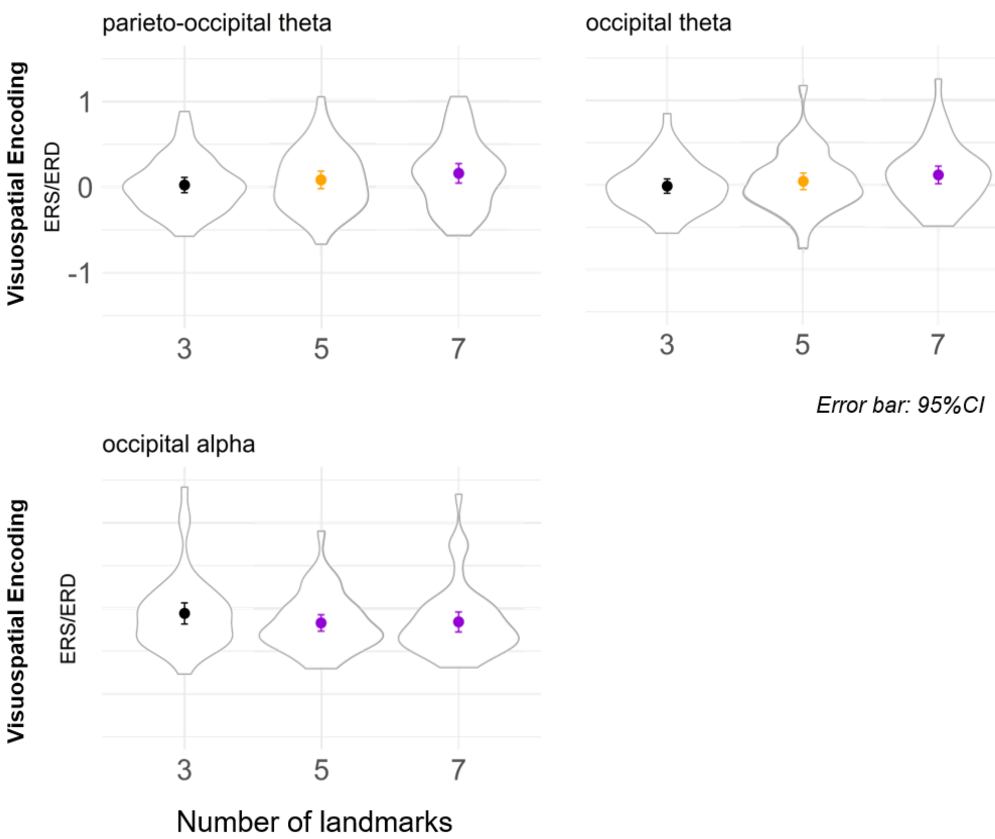


Figure 5.5 The three panels show the violin plots of parieto-occipital theta ERS (top-left), occipital theta ERS (top-right), and occipital alpha ERD (bottom) indicating visual and spatial encoding. Dots in the middle of the violin shapes indicate the means of each distribution of ERS/ERD values (i.e., the violin shapes). ERS and ERD were corrected to a pre-experiment baseline. Error bars indicate ± 1.96 standard error (i.e., 95% CI) of the mean. Colors of the means and error bars are coded as follows: means in the three-landmark condition are shown in black, serving as a baseline in each violin plot. Significant differences between means are presented with different colors within the same violin plot at $p < .05$. Means depicted in the same color within the same violin plot represent no significant difference between the means at $p \geq .05$.

5.3.5 Summary of brain activity during map consultation

In summary, cognitive load increased only when the seven landmarks were shown on the mobile map, compared to the other two landmark conditions, evidenced by the greater parieto-occipital P3 amplitude and fronto-central theta ERS. Visuospatial encoding increased continuously, when the number of landmarks increased from three, to five, and to seven, indicated by the corresponding increase in the posterior theta ERS. The findings presented in the section are discussed in Section 6.2.

Tables 5.2 and 5.3 below provide overviews of the regression coefficients and their statistical significance resulting from the aforementioned linear mixed-effect models on ERP components and power spectra.

Table 5.2 Regression coefficients of peak amplitudes of P3 at parietal-occipital leads and of P1 at occipital leads between the landmark conditions, resulting from the linear mixed-effect models. P-values highlighted in bold indicate significant differences at $p < .05$.

ROIs	Peak type	Cognitive process	Time window (ms)	LM condition contrast	β	95% CI	p
Parieto-occipital	P3	Cognitive load	450 – 750	5 vs 3	0.04	-0.92 – 1.00	.936
				7 vs 5	1.39	0.44 – 2.35	**.004**
Occipital	P1	Early visual encoding	80 – 150	5 vs 3	0.25	-0.38 – 0.88	.439
				7 vs 5	-0.47	-1.10 – 0.16	.139

Table 5.3 Linear regression coefficients resulting from the linear mixed-effect models of theta ERS and alpha ERD across the three landmark conditions. ERS and ERD were corrected to a pre-experiment baseline. P-values highlighted in bold indicate significant differences at $p < .05$.

ROIs	Frequency band	Cognitive process	LM condition contrast	β	95% CI	p
Fronto-central	theta	Cognitive load	5 vs 3	-0.03	-0.09 – 0.04	.391
			7 vs 5	0.10	0.04 – 0.16	**.002**
Parieto-occipital	theta	Visuospatial encoding	5 vs 3	0.06	0.01 – 0.11	**.027**
			7 vs 5	0.09	0.04 – 0.14	**.001**
	alpha	Cognitive load	5 vs 3	-0.03	-0.09 – 0.02	.220
			7 vs 5	-0.01	-0.06 – 0.05	.738
Occipital	theta	Visuospatial encoding	5 vs 3	0.06	0.01 – 0.11	**.027**
			7 vs 5	0.08	0.02 – 0.14	**.008**
	alpha	Visuospatial encoding	5 vs 3	-0.09	-0.16 – -0.03	**.006**
			7 vs 5	0.02	-0.05 – 0.09	.541

5.4 Effects of the number of landmarks on brain activity during locomotion

This section begins with a description of the number of blinks during locomotion—how many blinks participants generated while locomoting through the environments—to give readers a grasp of the blink events during active locomotion. The section then proceeds with the presentation of the brain activity in relation to the generated blink event markers. I first describe the characteristics of the obtained bERPs in the ROIs in relation to cognitive load and early visual encoding. I then present the findings of cognitive load during active locomotion, indicated by the blink-related N2 and P3 amplitude, as well as blink-related theta ERS and alpha ERD as converging evidence of bERPs. Finally, I present the results of bottom-up early-stage visual encoding in virtual environments, indicated by the blink-related N1 amplitude.

5.4.1 Number of blinks during locomotion

Participants generated on average 106.0 (SD = 13.0), 97.8 (SD = 10.8), and 111.0 (SD = 10.0) blinks in the three-, five-, and seven-landmark condition, respectively. The numbers of the detected blinks were compared between the three landmark conditions in the linear mixed-effect models and no significant difference was found (*ps* > .124).

5.4.2 Blink-related ERP characteristics

The blink-related potential at fronto-central leads demonstrated a positive component (P1), followed by a negative peak (N2). The blink-related potential at parieto-occipital leads showed a negative component (N1), followed by a positive component (P2) and a negative component (N2), and finally a P3-like peak. Finally, the blink-related potential at the occipital lead showed a clear negative component (N1), and the P2 component was not clearly presented. Subsequently, a clear P3-like component was shown at the occipital lead. The general characteristics of the blink-related N1, N2, and P3 are congruent with those in previous bERPs research (Wascher et al., 2014, 2022; Wunderlich & Gramann, 2020). The left panels of Figure 5.6 below illustrate the blink-related potential waves in the selected ROIs, i.e., fronto-central, parieto-occipital, and occipital regions, respectively.

5.4.3 Cognitive load–blink-related N2 and P3

The linear mixed-effect models showed that no significant difference was found in the blink-related N2 amplitude in the fronto-central region between the landmark conditions (5 vs. 3: $\beta = 0.01$, *95% CI* = [-0.35, 0.37], $p = .969$; 7 vs. 5: $\beta = 0.15$, *95% CI* = [-0.21, 0.51], $p = .415$).

The linear mixed-effect models showed that blink-related P3 amplitude in the parieto-occipital region did not change when the number of landmarks increased from three to five (5 vs. 3: $\beta = -0.01$, *95% CI* = [-0.40, 0.38], $p = .959$). The P3 amplitude increased significantly when seven landmarks were shown (7 vs. 5: $\beta = 0.41$, *95% CI* = [0.02, 0.80], p = .040).

Linear mixed-effect models revealed that no significant difference in the exploratory analysis (i.e., frontal theta ERS and parietal alpha ERD) was found between the landmark conditions (*ps* > .473).

5.4.4 Early visual encoding–blink-related N1

The linear mixed-effect models revealed that no significant difference was observed in blink-related N1 amplitude in the occipital region between the three landmark conditions (5 vs. 3: $\beta = -0.16$, *95% CI* = [-0.82, 0.51], $p = .649$; 7 vs. 5: $\beta = -0.23$, *95% CI* = [-0.90, 0.43], $p = .494$).

Figure 5.6 depicts the grand averaged amplitudes of bERPs at the selected ROIs (left panel) and the detected peak amplitude (right panel) of the bERP components for each landmark condition. Table 5.4 provides a comprehensive overview of the regression coefficients and their statistical significance resulting from the linear mixed-effect models of the bERP components (i.e., frontal-central N2, parieto-occipital P3, occipital N1).

5.4.5 Summary of blink-related brain activity

To summarize, cognitive load during locomotion possibly increased only when seven landmarks were shown on a mobile map compared to three and five landmarks, indicated by the greater amplitude of the blink-related P3 at parieto-occipital leads. However, another cognitive load indicator—fronto-central N2 amplitude at fronto-central leads did not differ between the three landmark conditions. Different numbers of landmarks depicted on a mobile map did not change bottom-up early-stage visual encoding during locomotion, evidenced by no difference in the blink-related N1 amplitude at the occipital lead. These findings are discussed in Section 6.3.

Table 5.4 Regression coefficients of peak amplitudes of the occipital N1, fronto-central N2, and parieto-occipital P3 across the landmark conditions. P-values in bold indicate significant differences at $p < .05$.

ROIs	Peak type	Cognitive process	Time window (ms)	LM condition contrast	β	95% CI	*p*
Fronto-central	N2	Cognitive load	250–390	5 vs 3	0.01	-0.35 – 0.37	.969
				7 vs 5	0.15	-0.21 – 0.51	. 415
Parieto-occipital	P3	Cognitive load	250–340	5 vs 3	-0.01	-0.40 – 0.38	.959
				7 vs 5	0.41	0.02 – 0.80	**.040**
Occipital	N1	Early visual encoding	110–150	5 vs 3	-0.16	-0.82 – 0.51	.649
				7 vs 5	-0.23	-0.90 – 0.43	.494

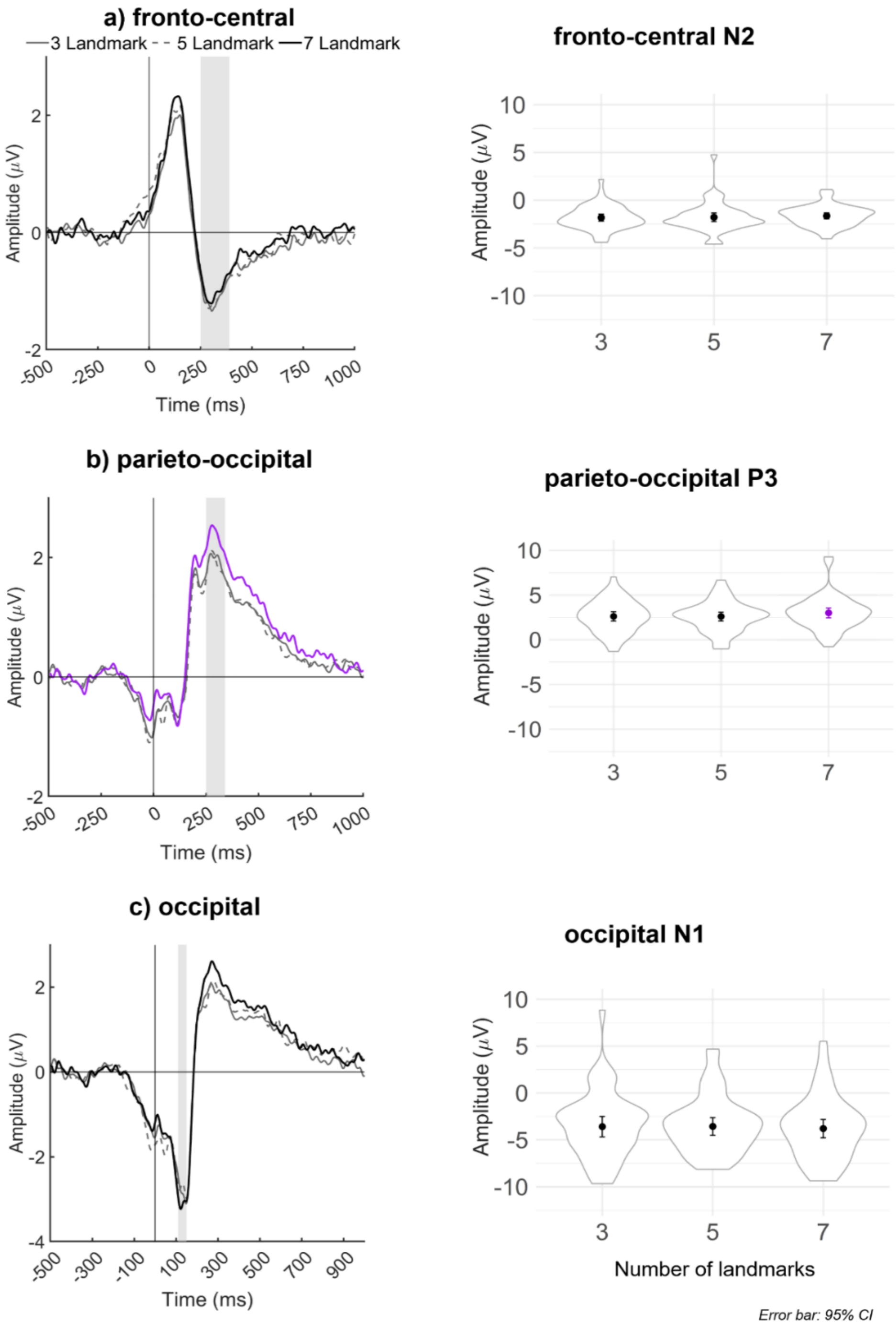


Figure 5.6 Left panel: Grand averaged amplitudes of bERPs for three landmark conditions at the a) fronto-central leads (Fz and FCz), b) parieto-occipital leads (Pz, POz, and Oz), and c) occipital lead (Oz). The bERP signals served as the basis for individual peak detection—areas shaded in gray indicate the time windows where the respective minima of fronto-central N2 (250–390 ms) and occipital N1 (110–150 ms) or maxima of the parieto-occipital P3 (250–340 ms) were identified. Right panel: violin plots showing the distribution of detected peak amplitudes together with mean and ±1.96 standard error (i.e., 95% CI) in each landmark condition for fronto-central N2, parieto-occipital P3, and occipital N1. Line in the left panel and mean in the right panel plotted in purple in the bottom panel indicate statistical significance at $p < .05$.

Chapter 6: Discussion

This chapter concerns in-depth discussions and interpretations of the results obtained from the map-assisted navigation experiment, which was set out to investigate the research questions of whether and how varying the number of landmarks depicted along a route on a mobile map during map-assisted navigation would influence navigators' spatial learning, cognitive load, and visuospatial encoding. In this chapter, I first critically review the findings in relation to the research questions and the related hypotheses and point out the related limitations in the current experiment (Sections 6.1, 6.2, and 6.3). Subsequently, I discuss the contributions of this thesis to the scientific research field in navigation and cognitive neuroscience as well as implications for mobile map design (Section 6.4). Finally, I suggest future research directions towards the development of user-supportive mobile navigation systems (Section 6.5).

6.1 Effects of the number of landmarks on spatial learning

In relation to the research question on the effects of the number of landmarks depicted on a mobile map on spatial learning, this thesis demonstrates that navigators' landmark and route learning performance improves when the number of landmarks shown on a mobile map increases from three (lowest evaluated number) to five (medium number), and their landmark and route learning performance does not further improve when seven (highest evaluated number) landmarks are shown. In line with the hypothesis of spatial learning (H1 in Section 3.2), these findings first suggest that depicting five landmarks on a mobile map during navigation can help navigators to recognize the landmarks along the route and better learn route directions in reference to these landmarks, compared to three landmarks. When presented with more landmarks on a mobile map, navigators may pay more attention to and encode these landmarks, the intersections, and the directions in reference to these landmarks on the map and in the environment, which in turn benefits spatial learning of the traversed route, as suggested in the landmark literature (e.g., Richter & Winter, 2014). In addition, the results further suggest that the benefit in spatial learning only holds to a certain number of landmarks (i.e., five landmarks in the current experiment). After exceeding this number, a further increase in the number of landmarks does not bring further benefits in landmark and route learning. This might be because presenting seven landmarks exceeds navigators' cognitive capacity and counterbalances the benefit of landmarks in spatial learning. This interpretation is discussed further in Section 6.2, in the context of EEG-measured cognitive load.

The observed effects of the number of landmarks shown on a mobile map during navigation on spatial learning are consistent with the literature on cognitive capacity showing that learning performance reaches a plateau after the number of learned items exceeds the learners' working memory capacity (Baddeley, 2003; Brady et al., 2019). The current findings further extend prior knowledge on cognitive capacity obtained with classic psychological experiments using simplified stimuli (e.g., colored squares, digits, etc.) to landmark and route learning capacity during naturalistic navigation in ecologically valid, yet well-controlled, virtual environments. The observed effects of the number of landmarks on spatial learning indicate that the cognitive capacity of most participants is saturated at five landmarks in my map-assisted navigation task. While learning landmarks in a visually complex and naturalistic setting, navigators receive and process rich visual and spatial cues from the environment and the map, which might help them to encode more landmarks and the directions with reference to these landmarks, compared to simplified and meaningless items. This is in line with the findings from Brady et al. (2019) that learners encode a real-world and meaningful object as a "feature ensemble" instead of encoding these features separately, which facilitates working memory processing and helps learners encode more task-relevant objects. Future studies should further examine which visual and spatial cues on the map or/and in the environments (e.g., landmark saliency, intersection structure) help navigators to encode landmarks and route directions.

The reported effects of the number of depicted landmarks can be applied to landmark and route knowledge and cannot be generalized to survey knowledge. In the current experiment, participants demonstrated high JRDs errors. This could be attributed to the current study design, in which the body-based cues, such as kinesthetic (the senses of position and movement of the body) and vestibular (sense of translational and rotational movement and body balance) senses (Gramann, 2013), were not integrated into participants' locomotion through the virtual environments. Such body-based cues have been known to facilitate survey knowledge acquisition (Chrastil & Warren, 2012). Another possibility could be that most navigators are not able to build reliable survey knowledge after navigating in a novel virtual environment only once (Frankenstein et al., 2012; Huffman & Ekstrom, 2018). Previous studies have shown that JRD performance improves with increasing navigation trials in the same environment (Huffman & Ekstrom, 2018; Zhang et al., 2014). As survey knowledge is useful for finding new routes and shortcuts, future studies should investigate the relationship between the number of displayed landmarks and survey knowledge acquisition by integrating more body-based cues (e.g., walking on a treadmill in VR, real-world study) and increasing navigators' exposure to an environment.

To further understand navigators' cognitive processing of different numbers of depicted landmarks, the following sections deal with how the landmark depiction influences cognitive load and visuospatial encoding indicated by established EEG parameters, while navigators are consulting a map and actively locomoting through the environment, respectively.

6.2 Effects of the number of landmarks on brain activity during map consultation

6.2.1 Cognitive load—P3 amplitude and theta ERS

Relating to the research question on how the number of landmarks depicted on a mobile map influences navigators' cognitive load while consulting the map, this research reports that both fronto-central theta ERS and parieto-occipital P3 amplitude increase along with the number of landmarks from five to seven depicted on a mobile map during map-assisted navigation, which is in line with the hypothesis of cognitive load (H2.1). Notably, theta ERS and P3 amplitude demonstrate the same pattern between the three landmark conditions in the current experiment. These results are consistent with previous literature showing a relationship between increasing task demands, greater frontal midline theta ERS (e.g., Krause et al., 2000; Maurer et al., 2015; Scharinger et al., 2017), and more pronounced posterior P3 amplitude (e.g., Kok, 2001; Polich, 2007; Scharinger et al., 2017; Wei & Zhou, 2020). By reporting the same effect on frontal midline theta power and posterior P3 amplitude in a naturalistic scenario of map-assisted navigation, this thesis extends the existing knowledge of a task's cognitive demands measured by EEG usually using simplified cognitive tasks (e.g., remembering digits or squares) to a naturalistic navigation context.

Importantly, theta ERS and P3 amplitude are determined not only by the amount of presented information that needs processing (i.e., intrinsic task demands), but also by the internal expenditure of cognitive resources on a cognitive task at hand (Kok, 2001; Näätänen, 1992; Onton et al., 2005). The EEG results in the context of map-assisted navigation suggest that navigators' cognitive load does not increase while processing the five landmarks shown on a mobile map compared to three landmarks and indicate that showing the medium amount of landmarks (i.e., five) does not require additional cognitive effort, compared to the lowest evaluated amount of landmarks (i.e., three). This might be because of the benefit of landmarks in spatial learning—presenting more landmarks on the mobile map facilitates learning of the traversed environment. And yet, showing the highest number of landmarks (i.e., seven) increases cognitive load, suggesting that navigators exert more cognitive resources when processing seven landmarks, compared to the other two landmark conditions. These findings together suggest presenting the medium number of landmarks (i.e., five landmarks in the current experiment) is the option that might best improve navigators' spatial learning outcome without additionally taxing cognitive resources.

However, this thesis does not find any differences in posterior alpha ERD—an EEG parameter indicating cognitive load—between the experimental conditions, which does not support the hypothesis on cognitive load (H2.1). One possible reason for this is the conflicting relationships between posterior alpha ERD and cognitive load reported in recent years (Jensen & Mazaheri, 2010; Palva & Palva, 2007). Recent research has proposed that alpha ERS and alpha ERD might be associated with two different cognitive mechanisms—attention orientation and attention maintenance, respectively (Capilla et al., 2014; Puma et al., 2018). These two mechanisms both occur during the map-assisted navigation task and are not distinguished by the current study design. Therefore, alpha ERS and alpha ERD might have both occurred and canceled each other out in the extracted alpha power spectra during map consulting.

6.2.2 Visuospatial encoding—theta ERS and alpha ERD

As maps are spatial arrays containing visual information and landmarks contain both visual and spatial information, it is also important to examine navigators' visuospatial encoding while they are viewing the maps. In line with the hypothesis of visuospatial encoding (H2.2), along with increasing amounts of landmarks displayed on a mobile map, theta ERS at both parieto-occipital and occipital leads increases, which is congruent with the findings of previous studies on posterior theta power changes during human spatial navigation (Do et al., 2021; Fischer et al., 2020) and visual stimuli encoding (Delaux et al., 2021; Y. K. Wang et al., 2018), respectively. These findings suggest that when more landmarks are available for visuospatial encoding on a mobile map, brain activity related to visuospatial encoding increases accordingly. Occipital alpha ERD also shows a significant global increasing tendency with increasing the number of landmarks, but it does not differ significantly from five to seven landmarks. This is consistent with the previous study (Scharinger et al., 2017) showing that alpha ERD discriminates between the low-load and medium-load conditions but not between medium-load and high-load conditions.

Together with the results on cognitive load discussed in the foregoing section, these findings suggest that an increase in available visuospatial information on mobile maps (i.e., when the number of landmarks increases from three to five) does not necessarily lead to an increase in cognitive load.

6.3 Effect of the number of landmarks on brain activity during locomotion

6.3.1 Cognitive load—blink-related P3 and N2

In reference to the research question on the relationship between the number of landmarks displayed on a mobile map and navigators' cognitive load during active locomotion, this thesis observes that the blink-related parietal-occipital P3 component of navigators increases during active locomotion after participants have viewed more landmarks on a mobile map, which supports the hypothesis of increasing cognitive load during active locomotion when more landmarks are depicted on mobile maps (H3.1). A recent bERP study by Wascher et al. (2022) suggested that blink-related posterior P3 component is associated with attentional resource distribution, whereby an increased blink-related P3 amplitude reflects more attentional resources being exerted on one task in a dual-task paradigm. The finding of blink-related P3 in the current thesis indicates that more attentional resources are taxed when navigating through the environment in the seven-landmark condition, compared to the three- and five-landmark conditions. The result of the blink-related posterior P3 component is also in line with those in the ERP research on stimulus-based posterior P3, discussed in Section 6.2.1. To further validate the results and interpretations of EEG/ERP modulations reflecting cognitive load in navigation contexts, future research should combine other instruments to assess cognitive load, such as self-reports using the NASA-TLX questionnaire (Hart & Staveland, 1988) and pupil diameter measurements using mobile eye trackers (Krejtz et al., 2018).

No difference in the blink-related fronto-central N2 amplitude is observed between the three landmark conditions, which does not support the hypothesis of cognitive load during locomotion (H3.1). Blink-related fronto-central N2 has been proposed to reflect top-down information processing by examining the N2 component between the cognitive load and no-load conditions (Wascher et al., 2014, 2022). One interpretation for the obtained result on the blink-related N2 component could be that the blink-based N2 component is not sensitive enough to distinguish different levels of cognitive load designed in the current experiment. Another attribution might be because the stimulus-evoked frontal midline N2 component is usually a neural indicator for cognitive control and mismatch (Folstein & Van Petten, 2008), which is not relevant to the study design in this thesis. Future work is needed to further analyze the relationship between blink-related frontal midline N2 component and cognitive load.

6.3.2 Early visual encoding—blink-related N1

No significant difference is observed in the blink-related N1 amplitude at the occipital lead between the three landmark conditions, in line with our hypothesis of early visual encoding during locomotion (H3.2). This result indicates that showing different numbers of landmarks on a mobile map does not affect participants' early bottom-up visual perception when they move through the environments without looking at the map. This is because participants are locomoting in the same environment and receive the same bottom-up visual stimuli from the environment. However, large variances of the detected peak amplitudes of the occipital N1 component are observed in this thesis, and it is consistent with the large variance of the occipital N1 component in prior bERP studies by Wascher et al. (2014, 2022).

Therefore, the use of blink-related N1 to indicate visual encoding requires further investigation in future research.

6.4 Contributions

First, this thesis contributes to scientific knowledge in the field of human navigation and landmark research by providing further insights into the role of landmarks depicted on mobile maps in navigators' spatial learning and cognitive load during navigation. Taking the results of spatial learning and cognitive load together, it seems that depicting a medium number of landmarks on a mobile map improves spatial learning without taxing additional cognitive efforts, compared to presenting the lowest number of landmarks. Previous literature has addressed the important role of landmarks in spatial navigation and spatial knowledge acquisition (e.g., Raubal & Winter, 2002). This thesis further extends the understanding of the benefit of landmarks for navigation and spatial learning and suggests a potential boundary of this benefit—that is, presenting more landmarks on a mobile map improves navigators' spatial learning only when the number of presented landmarks does not exceed navigators' cognitive capacity during navigation. This also provides an important message for cartographers and navigation assistance developers that they should consider and evaluate individuals' cognitive capacity to process landmark information when providing landmarks during assisted navigation.

Furthermore, this thesis extends the existing knowledge in the academic discipline of cartography by sharing insights on how visuospatial information presented on a mobile map is processed by navigating map users, and how this visuospatial information can assist navigation and spatial learning. The findings on the visuospatial encoding of the map information, the induced cognitive load, and spatial learning together suggest that an increase of available visuospatial information (from three to five landmarks) on a mobile map during navigation leads to a corresponding increase in the brain activity associated with visuospatial encoding, but not necessarily an increase in cognitive load or spatial learning performance.

The current research, thus, extends the existing literature on cognitive cartographic research by identifying that two different cognitive processes are involved during map-assisted navigation (Allen, 2003; Lobben, 2004; Montello, 2002). Mobile map designers and cartographers should consider and evaluate how visual information presentation on a map influences visual and spatial processing demand (Garlandini & Fabrikant, 2009) and cognitive load (Bunch & Lloyd, 2006).

Third, this thesis makes methodological contributions to the field of human-computer interaction (HCI), part of which investigates users' interactions with navigation assistance devices (Savino et al., 2020, 2021), by addressing the interplay between interface design, neuroscientific methods, and behavioral assessments during map-assisted navigation. In the research field of navigation assistance development, behavioral measurements and eye-tracking systems are commonly employed to examine users' interaction with the device and how the interaction influences users' behavior (Göbel et al., 2019). Recently, there has been increasing attention on using neuroscientific methods to investigate map-assisted navigation (e.g., J. Liu et al., 2022), though these research studies remain sparse. Neurocognitive methods are a useful tool to capture users' ongoing cognitive processing and their changing cognitive states while they are interacting with mobile devices, which is critical for designing cognitively supportive navigation devices. Furthermore, this thesis employs a relatively novel method using blinks as event markers to parse individuals' brain activity while they are not consulting the device. The findings of this thesis imply a possible cognitive load spillover effect—cognitive states during map use and those outside of map use during locomotion might affect each other. This has an important implication for user-centered navigation system developers that navigators' cognitive processing and cognitive states outside of the mobile navigation device use should be also considered and evaluated when developing a user-supportive navigation system.

6.5 Limitations and future research

To validate and generalize the findings of the current dissertation, future research should increase the ecological validity of navigation scenarios and examine different navigation scenarios in different environments. More detailed discussions on limitations and concrete suggestions for future research are the subjects of what follows.

First, this thesis provides the first evidence of a relationship between the number of depicted landmarks on a mobile map, cognitive load, and spatial learning during map-assisted navigation. The selection of three versus five versus seven landmarks following classic literature on cognitive capacity (e.g., Baddeley, 2003; Brady et al., 2016) turns out to be a useful springboard for future research on landmark visualization on mobile maps during navigation. Future research should further investigate whether this relationship is monotonic or discrete. In particular, it would be worthwhile to examine how spatial learning and cognitive load change with four, six, and beyond seven landmarks—whether spatial learning already reaches a plateau with four (instead of five) or learning performance continues to increase from five to six landmarks and then drops beyond seven landmarks. This will provide a more comprehensive understanding of the relationship between the number of landmarks, spatial learning, and cognitive load and contribute to the development of a neuroadaptive mobile map that gradually adapts the number of landmarks based on users' cognitive load to optimize their spatial learning.

Second, the reported relationships between the number of landmarks, spatial learning, and cognitive load may be restricted to the specific settings in the current experiment, such as the length of routes, the type of cities, and the employed map stimuli. The current study controlled the length of the routes from 880m to 950m with five intersections and adopted grid-like street layouts. Previous literature suggested that environmental features, such as complexities of street networks and openness of environments, influenced navigators' wayfinding and spatial learning (Coutrot et al., 2022; Miola et al., 2021; Wiener & Pazzaglia, 2021). A series of future studies could follow the current experiment paradigm and examine whether this reported relationship still holds in different types of environments, for example, with different lengths of routes and different complexities of the environment (e.g., street layouts, environmental styles). Besides, in the current experiment, the landmarks were presented one by one at each intersection on track-up maps which align with navigators' heading direction. Future studies should investigate other commonly used navigation map styles, such as north-up maps.

Furthermore, to control the effects of age and education on spatial learning, the current experiment tested young (18 - 36 years old) and relatively well-educated (tertiary education) adults. Previous literature suggested that both spatial abilities and cognitive capacity changed across the lifespan. Therefore, elderly people might remember less than five landmarks in the current experiment, as their spatial abilities and memory capacity decline compared to the young adults (Hartshorne & Germine, 2015; Spiers et al., 2023; van der Ham et al., 2020). Other factors that future studies should evaluate are individuals' education and training backgrounds, as studies have shown that the level of education and STEM (Science, Technology, Engineering, Mathematics) education are positively correlated with spatial abilities (Coutrot et al., 2022; Uttal & Cohen, 2012). Future studies should fully consider and investigate the roles of ages and educational backgrounds using the current experiment paradigm to generalize the obtained results on the number of landmarks to a broader population.

Moreover, the reported effects of the number of landmarks on cognitive load and spatial learning are obtained based on a single navigation trial in an unfamiliar environment. One important follow-up research question is whether and how these reported effects change with multiple exposures to the same environment (i.e., increased familiarity with the environment) and how this experience increases spatial learning or decreases cognitive load over time (e.g., weeks, months), as navigators traverse the same environment multiple times in the real world. Indeed, navigators are able to acquire more landmark, route, and survey knowledge of the traversed environment after multiple exposures to the same environment

(Kim & Bock, 2021). Moreover, existing research on agent-based modeling has shown that adapting abstraction levels of landmark and route information in navigation instructions based on a navigator's existing knowledge about the environment facilitated navigation efficiency (Teimouri & Richter, 2022). Thus, future work should also focus on landmark depictions on a mobile map based on navigators' prior knowledge of the environment.

Finally, future studies on mobile map-aided navigation in the real world are needed in order to apply the current findings to real-world use cases. Although we used ecologically valid stimuli and simulate the movement with a foot pedal to enable partial body-based cues, motor, vestibular, and proprioceptive cues are limited when navigating in a virtual environment, which has been known to facilitate navigation and spatial learning (Chrastil & Warren, 2012; Gramann et al., 2021; Klatzky, 1998). A real-world study may be able to reveal more ecologically valid discoveries about how these physical movements modulate the reported effects of the number of landmarks displayed on mobile maps on spatial learning (especially survey knowledge) and cognitive load. Notably, for real-world neuroscience research, there is a lack of control over participants' behavior (e.g., when and how frequently they use the mobile map) and environmental factors (e.g., wind influences blinks). To tackle the methodological challenges, future studies should consider coupling EEG with eye-tracking to obtain more information on users' eye behavior, such as their gaze fixation in the environment and on the mobile map. Such information on the focal stimuli can help researchers to categorize their blinks and attention and to interpret the results of brain activity and behavioral performance.

Chapter 7: Conclusions

In the digital age, mobile GPS-enabled navigation devices are increasingly used to support navigation. Although such devices facilitate some aspects of navigation (e.g., self-localization), there is ample evidence of their negative effects on the spatial knowledge acquisition about the environments traversed. To counteract the induced negative consequences of mobile navigation devices on spatial learning, this thesis provides a solution of including landmarks on mobile maps during assisted navigation. Landmarks, as widely proposed in navigation research, play a key role in assisting navigation and environmental learning. Meanwhile, the literature on cognitive capacity suggests that individuals have limited cognitive resources to process presented information and that their learning performance may reach a plateau or even decline after the number of learned items exceeds their capacity. Hence, it is important to provide a cognitively usable set of landmarks that optimizes navigators' cognitive resource exertion and spatial learning. This thesis set out a VR navigation experiment, in which participants followed a given route visualized on a mobile map and were instructed to learn landmarks along the route. The experiment first examined how the display of three different numbers (3 versus 5 versus 7) of landmarks on a mobile map affected navigators' spatial learning, as evaluated by three spatial learning tests. In addition, EEG was employed to assess how the landmark depiction on a mobile map influenced navigators' cognitive load and visuospatial encoding during map consultation as well as during active locomotion. Statistical results reveal that 1) landmark and route learning, but not survey learning, improved when five landmarks were depicted on a mobile map compared to three landmarks, and there was no further improvement when seven landmarks were provided; 2) cognitive load increased when participants were processing seven landmarks depicted on mobile maps compared to the other two landmark conditions, as evidenced by greater frontal-central theta synchronization and greater parieto-occipital P3 amplitude; by contrast, visuospatial encoding increases with the increased number of presented landmarks accordingly, as indicated by more pronounced posterior theta synchronization; 3) cognitive load increased in the seven-landmark condition, when participants were locomoting through the environment and not viewing the map, compared to the other two landmark conditions, as evidenced by greater blink-related P3 amplitude at parieto-occipital leads. Taken together, these results provide a better understanding of the effects of landmark depiction on spatial learning and cognitive load during map-assisted navigation. Finally, this thesis also provides an example of how to investigate and solve a cartographic design problem by leveraging neuropsychological approaches. The experiment and the findings reveal that neuropsychological tools are useful for understanding users' behavior and related neural mechanisms and for designing user-centered and cognitively supportive devices. Below, I discuss two main takeaways for the readers, based on the findings of this thesis.

7.1 Main takeaways

First, providing a medium number of landmarks (i.e., five landmarks) on a mobile map during navigation is the best option, as it improves navigators' spatial learning performance and does not tax additional cognitive resources. This thesis supports the proposed benefit of landmarks in navigation and spatial learning and additionally suggests *a boundary* of this benefit of landmarks: visualizing landmarks on a mobile map benefits users' spatial learning only to a certain extent—when the number of visualized landmarks does not increase cognitive load.

Second, cognitive load during map use and those during locomotion influence each other. During map-assisted navigation, locomoting through an environment to reach a specific intersection or place (e.g., titling the foot controller to steer the movement in the current experiment) is related to intrinsic cognitive load. Depicting more landmarks on a mobile map leads to better spatial memory, which is possibly associated with germane cognitive load, as landmarks at the traversed intersections are relevant to the navigation task at hand. Therefore, the increased cognitive load might be *spilled over* between the germane load during map viewing and the intrinsic load during locomotion in the environment. The increased cognitive load during both navigational phases might explain the boundary of the benefit of landmarks on mobile maps in spatial learning.

7.2 Outlook on human spatial navigation in the digital era

This thesis provides an exemplary paradigm of leveraging neuropsychological approaches to answer a cartographic design and societal problem—how to counteract the negative effects of GPS-enabled navigation devices on users' navigational skills and spatial memory? This thesis provides a possible solution by visualizing different numbers of landmarks based on navigators' cognitive load to improve their spatial learning of the traversed environment. To further validate and generalize the work and the results, researchers and practitioners should focus on the following aspects in the future.

First, a continuous relationship between the number of landmarks and spatial learning and cognitive load should be investigated, which is crucial for the development of a neuroadaptive mobile map that adapts the landmarks on mobile maps gradually, based on navigators' ongoing cognitive load, and optimizes their spatial learning. In addition, to obtain a more comprehensive understanding of the relationship between the number of landmarks, cognitive load, and spatial learning, future research and design practice should examine different environments and environmental features (e.g., different route lengths, different street layouts) and also include navigators' prior knowledge of the environment. Moreover, an ecological study in the real world is needed to apply these findings to a real-world design and use cases.

Finally, this thesis points to a broader direction for future research agendas and design practices that tackle the same societal problem of the negative effects of GPS-enabled navigation devices on users' navigational skills and spatial memory. It is important to keep in mind that assisted navigation is a dynamic interaction between the navigator, the device, and the environment (Ishikawa, 2020; p. 157). Navigation aids should, on the one hand, be designed to support the navigation task itself, such as providing directions to reach a destination. More importantly, on the other hand, other factors in this dynamic loop, such as users' abilities and states (e.g., cognitive load and spatial skills), and their interaction with and knowledge of an environment, should be well considered, evaluated, and included in the design process. GPS technologies should promote physical and social engagement with environments, people, and experiences, as Aporta & Higgs (2005) noted in their research on Inuit wayfinding and GPS technology.

References

Allen, G. L. (1999). Spatial abilities, cognitive maps, and wayfinding: Bases for individual differences in spatial cognition and behavior. In *Wayfinding behavior: Cognitive mapping and other spatial processes* (R. G. Golledge, pp. 46–80). Johns Hopkins University Press.

Allen, G. L. (Ed.). (2003). *Human Spatial Memory: Remembering Where*. Psychology Press. https://doi.org/10.4324/9781410609984

Allison, S. L., Fagan, A. M., Morris, J. C., & Head, D. (2016). Spatial Navigation in Preclinical Alzheimer's Disease. *Journal of Alzheimer's Disease: JAD*, *52*(1), 77–90. https://doi.org/10.3233/JAD-150855

Anacta, V. J. A., Schwering, A., Li, R., & Muenzer, S. (2017). Orientation information in wayfinding instructions: Evidences from human verbal and visual instructions. *GeoJournal*, *82*(3), 567–583. https://doi.org/10.1007/s10708-016-9703-5

Aporta, C., & Higgs, E. (2005). Satellite Culture: Global Positioning Systems, Inuit Wayfinding, and the Need for a New Account of Technology. *Current Anthropology*, *46*(5), 729–753. https://doi.org/10.1086/432651

Armougum, A., Orriols, E., Gaston-Bellegarde, A., Marle, C. J. L., & Piolino, P. (2019). Virtual reality: A new method to investigate cognitive load during navigation. *Journal of Environmental Psychology*, *65*, 101338. https://doi.org/10.1016/j.jenvp.2019.101338

Awh, E., Anllo-Vento, L., & Hillyard, S. A. (2000). The Role of Spatial Selective Attention in Working Memory for Locations: Evidence from Event-Related Potentials. *Journal of Cognitive Neuroscience*, *12*(5), 840–847. https://doi.org/10.1162/089892900562444

Baddeley, A. (2003). Working memory: Looking back and looking forward. *Nature Reviews Neuroscience*, *4*(10), 829–839. https://doi.org/10.1038/nrn1201

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*, *68*(3), 255–278. https://doi.org/10.1016/j.jml.2012.11.001

Bates, D., Maechler, M., Bolker, B., Walker, S., Christensen, R. H. B., Singmann, H., Dai, B., Scheipl, F., & Grothendieck, G. (2011). Package 'lme4.' *Linear Mixed-Effects Models Using S4 Classes. R Package Version*, *1*. http://dk.archive.ubuntu.com/pub/pub/cran/web/packages/lme4/lme4.pdf

Bednar, J., Chen, Y., Liu, T. X., & Page, S. (2012). Behavioral spillovers and cognitive load in multiple games: An experimental study. *Games and Economic Behavior*, *74*(1), 12–31. https://doi.org/10.1016/j.geb.2011.06.009

Berg, P., & Davies, M. B. (1988). Eyeblink-related potentials. *Electroencephalography and Clinical Neurophysiology*, *69*, 1–5.

Blacker, K. J., Weisberg, S. M., Newcombe, N. S., & Courtney, S. M. (2017). Keeping track of where we are: Spatial working memory in navigation. *Visual Cognition*, *25*(7–8), 691–702. https://doi.org/10.1080/13506285.2017.1322652

Bohbot, V. D., Copara, M. S., Gotman, J., & Ekstrom, A. D. (2017). Low-frequency theta oscillations in the human hippocampus during real-world and virtual navigation. *Nature Communications*, *8*, 1–7. https://doi.org/10.1038/ncomms14415

Brady, T. F., Störmer, V. S., & Alvarez, G. A. (2016). Working memory is not fixed-capacity: More active storage capacity for real-world objects than for simple stimuli. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(27), 7459–7464. https://doi.org/10.1073/PNAS.1520027113/-/DCSUPPLEMENTAL

Brady, T. F., Störmer, V. S., Shafer-Skelton, A., Williams, J. R., Chapman, A. F., & Schill, H. M. (2019). Scaling up visual attention and visual working memory to the real world. In *Psychology of Learning and Motivation—Advances in Research and Theory* (Vol. 70, pp. 29–69). https://doi.org/10.1016/bs.plm.2019.03.001

Brügger, A., Richter, K. F., & Fabrikant, S. I. (2019). How does navigation system behavior influence human behavior? *Cognitive Research: Principles and Implications*, *4*(1), 5. https://doi.org/10.1186/s41235-019-0156-5

Bulling, A., Ward, J. A., Gellersen, H., & Tröster, G. (2011). Eye Movement Analysis for Activity Recognition Using Electrooculography. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *33*(4), 741–753. https://doi.org/10.1109/TPAMI.2010.86

Bunch, R., & Lloyd, R. (2006). The Cognitive Load of Geographic Information. *The Professional Geographer*, *58*, 209–220. https://doi.org/10.1111/j.1467-9272.2006.00527.x

Burte, H., & Montello, D. R. (2017). How sense-of-direction and learning intentionality relate to spatial knowledge acquisition in the environment. *Cognitive Research: Principles and Implications*, *2*(1), 18. https://doi.org/10.1186/s41235-017-0057-4

Capilla, A., Schoffelen, J. M., Paterson, G., Thut, G., & Gross, J. (2014). Dissociated α-Band Modulations in the Dorsal and Ventral Visual Pathways in Visuospatial Attention and Perception. *Cerebral Cortex*, *24*(2), 550–561. https://doi.org/10.1093/CERCOR/BHS343

Chan, E., Baumann, O., Bellgrove, M., & Mattingley, J. (2012). From Objects to Landmarks: The Function of Visual Location Information in Spatial Navigation. *Frontiers in Psychology*, *3*. https://www.frontiersin.org/articles/10.3389/fpsyg.2012.00304

Chandler, P., & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction*, *8*, 293–332. https://doi.org/10.1207/s1532690xci0804_2

Chrastil, E. R. (2013). Neural evidence supports a novel framework for spatial navigation. *Psychonomic Bulletin & Review*, *20*(2), 208–227. https://doi.org/10.3758/s13423-012-0351-6

Chrastil, E. R., & Warren, W. H. (2012). Active and passive contributions to spatial learning. *Psychonomic Bulletin and Review*, *19*(1), 1–23. https://doi.org/10.3758/s13423-011-0182-x

Clemenson, G. D., Maselli, A., Fiannaca, A. J., Miller, A., & Gonzalez-Franco, M. (2021). Rethinking GPS navigation: Creating cognitive maps through auditory clues. *Scientific Reports 2021 11:1*, *11*(1), 1–10. https://doi.org/10.1038/s41598-021-87148-4

Cohen, M. X. (2014). *Analyzing Neural Time Series Data: Theory and Practice*. MIT Press.

Coluccia, E., Bosco, A., & Brandimonte, M. A. (2007). The role of visuo-spatial working memory in map learning: New findings from a map drawing paradigm. *Psychological Research*, *71*(3), 359–372. https://doi.org/10.1007/S00426-006-0090-2/TABLES/4

Coughlan, G., Laczó, J., Hort, J., Minihane, A. M., & Hornberger, M. (2018). Spatial navigation deficits—Overlooked cognitive marker for preclinical Alzheimer disease? *Nature Reviews Neurology*, *14*(8), 496–506. https://doi.org/10.1038/s41582-018-0031-x

Coughlan, G., Puthusseryppady, V., Lowry, E., Gillings, R., Spiers, H., Minihane, A.-M., & Hornberger, M. (2020). Test-retest reliability of spatial navigation in adults at-risk of Alzheimer's disease. *PLOS ONE*, *15*(9), e0239077. https://doi.org/10.1371/journal.pone.0239077

Coutrot, A., Manley, E., Goodroe, S., Gahnstrom, C., Filomena, G., Yesiltepe, D., Dalton, R. C., Wiener, J. M., Hölscher, C., Hornberger, M., & Spiers, H. J. (2022). Entropy of city street networks linked to future spatial navigation ability. *Nature*, *604*(7904), Article 7904. https://doi.org/10.1038/s41586-022-04486-7

Credé, S., Thrash, T., Hölscher, C., & Fabrikant, S. I. (2019). The acquisition of survey knowledge for local and global landmark configurations under time pressure. *Spatial Cognition & Computation*, 1–30. https://doi.org/10.1080/13875868.2019.1569016

Credé, S., Thrash, T., Hölscher, C., & Fabrikant, S. I. (2020). The advantage of globally visible landmarks for spatial learning. *Journal of Environmental Psychology*, *67*. https://doi.org/10.1016/j.jenvp.2019.101369

Dahmani, L., & Bohbot, V. D. (2020). Habitual use of GPS negatively impacts spatial memory during self-guided navigation. *Scientific Reports 2020 10:1*, *10*(1), 1–14. https://doi.org/10.1038/s41598-020-62877-0

Darken, R. P., & Peterson, B. (2002). Spatial Orientation, Wayfinding, and Representation. In *Handbook of Virtual Environments*. CRC Press. https://doi.org/10.1201/9780585399102

Deeny, S., Chicoine, C., Hargrove, L., Parrish, T., & Jayaraman, A. (2014). A Simple ERP Method for Quantitative Analysis of Cognitive Workload in Myoelectric Prosthesis Control and Human-Machine Interaction. *PLOS ONE*, *9*(11), e112091. https://doi.org/10.1371/journal.pone.0112091

Delaux, A., de Saint Aubert, J. B., Ramanoël, S., Bécu, M., Gehrke, L., Klug, M., Chavarriaga, R., Sahel, J. A., Gramann, K., & Arleo, A. (2021). Mobile brain/body imaging of landmark-based navigation with high-density EEG. *European Journal of Neuroscience*. https://doi.org/10.1111/ejn.15190

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Denis, M., & Fernandez, G. (2013). The processing of landmarks in route directions. In T. Tenbrink, J. M. Wiener, & C. Claramunt (Eds.), *Representing Space in Cognition: Interrelations of behaviour, language, and formal models* (p. 0). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199679911.003.0004

Do, T. T. N., Lin, C. T., & Gramann, K. (2021). Human brain dynamics in active spatial navigation. *Scientific Reports 2021 11:1*, *11*(1), 1–12. https://doi.org/10.1038/s41598-021-92246-4

Doesburg, S. M., Green, J. J., McDonald, J. J., & Ward, L. M. (2009). From local inhibition to long-range integration: A functional dissociation of alpha-band synchronization across cortical scales in visuospatial attention. *Brain Research*, *1303*, 97–110. https://doi.org/10.1016/j.brainres.2009.09.069

Dong, S., Reder, L. M., Yao, Y., Liu, Y., & Chen, F. (2015). Individual differences in working memory capacity are reflected in different ERP and EEG patterns to task difficulty. *Brain Research*, *1616*, 146–156. https://doi.org/10.1016/J.BRAINRES.2015.05.003

Dressler, O., Schneider, G., Stockmanns, G., & Kochs, E. F. (2004). Awareness and the EEG power spectrum: Analysis of frequencies. *BJA: British Journal of Anaesthesia*, *93*(6), 806–809. https://doi.org/10.1093/bja/aeh270

Duckham, M., Winter, S., & Robinson, M. (2010). Including landmarks in routing instructions. *Journal of Location Based Services*, *4*(1), 28–52. https://doi.org/10.1080/17489721003785602

Ehinger, B. V., & Dimigen, O. (2019). Unfold: An integrated toolbox for overlap correction, non-linear modeling, and regression-based EEG analysis. *PeerJ*, *7*(e7838). https://doi.org/10.7717/peerj.7838

Ekstrom, A. D., Arnold, A. E. G. F., & Iaria, G. (2014). A critical review of the allocentric spatial representation and its neural underpinnings: Toward a network-based perspective. *Frontiers in Human Neuroscience*, *8*(OCT), 803. https://doi.org/10.3389/FNHUM.2014.00803/BIBTEX

Ekstrom, A. D., & Ranganath, C. (2018). Space, time, and episodic memory: The hippocampus is all over the cognitive map. *Hippocampus*, *28*(9), 680–687. https://doi.org/10.1002/hipo.22750

Enders, L. R., Smith, R. J., Gordon, S. M., Ries, A. J., & Touryan, J. (2021). Gaze Behavior During Navigation and Visual Search of an Open-World Virtual Environment. *Frontiers in Psychology*, *12*, 681042. https://doi.org/10.3389/fpsyg.2021.681042

Endress, A. D., & Potter, M. C. (2014). Large capacity temporary visual memory. *Journal of Experimental Psychology: General*, *143*, 548–565. https://doi.org/10.1037/a0033934

Epstein, R. A., & Vass, L. K. (2014). Neural systems for landmark-based wayfinding in humans. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *369*(1635). https://doi.org/10.1098/rstb.2012.0533

Evans, G. W., Smith, C., & Pezdek, K. (1982). Cognitive Maps and Urban Form. *Journal of the American Planning Association*, *48*(2), 232–244. https://doi.org/10.1080/01944368208976543

Felisberti, F. M., & Fernandes, T. P. (2022). *The interplay between cognitive load and driving in scenarios of daily commuting*. PsyArXiv. https://doi.org/10.31234/osf.io/3xqcj

Fenech, E. P., Drews, F. A., & Bakdash, J. Z. (2010). The Effects of Acoustic Turn-by-turn Navigation on Wayfinding. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *54*(23), 1926–1930. https://doi.org/10.1177/154193121005402305

Fischer, L. F., Mojica Soto-Albors, R., Buck, F., & Harnett, M. T. (2020). Representation of visual landmarks in retrosplenial cortex. *ELife*, *9*, e51458. https://doi.org/10.7554/eLife.51458

Folstein, J. R., & Van Petten, C. (2008). Influence of cognitive control and mismatch on the N2 component of the ERP: A review. *Psychophysiology*, *45*(1), 152–170. https://doi.org/10.1111/j.1469-8986.2007.00602.x

Frankenstein, J., Mohler, B. J., Bülthoff, H. H., & Meilinger, T. (2012). Is the Map in Our Head Oriented North? *Psychological Science*, *23*(2), 120–125. https://doi.org/10.1177/0956797611429467

Frissen, I., Campos, J. L., Souman, J. L., & Ernst, M. O. (2011). Integration of vestibular and proprioceptive signals for spatial updating. *Experimental Brain Research*, *212*(2), 163–176. https://doi.org/10.1007/s00221-011-2717-9

Fu, S., & Parasuraman, R. (2006). Event-Related Potentials (ERPs) in Neuroergonomics. In R. Parasuraman & M. Rizzo (Eds.), *Neuroergonomics: The brain at work* (pp. 32–50). Oxford Academic.

Fukuda, K., Mance, I., & Vogel, E. K. (2015). α Power Modulation and Event-Related Slow Wave Provide Dissociable Correlates of Visual Working Memory. *Journal of Neuroscience*, *35*(41), 14009–14016. https://doi.org/10.1523/JNEUROSCI.5003-14.2015

Gabrio, A., Plumpton, C., Banerjee, S., & Leurent, B. (2022). Linear mixed models to handle missing at random data in trial-based economic evaluations. *Health Economics*, *31*(6), 1276–1287. https://doi.org/10.1002/hec.4510

Garden, S., Cornoldi, C., & Logie, R. H. (2002). Visuo-spatial working memory in navigation. *Applied Cognitive Psychology*, *16*(1), 35–50. https://doi.org/10.1002/ACP.746

Gardony, A. L., Brunyé, T. T., Mahoney, C. R., & Taylor, H. A. (2013). How Navigational Aids Impair Spatial Memory: Evidence for Divided Attention. *Spatial Cognition and Computation*, *13*(4), 319–350. https://doi.org/10.1080/13875868.2013.792821

Gardony, A. L., Brunyé, T. T., & Taylor, H. A. (2015). Navigational aids and spatial memory impairment: The role of divided attention. *Spatial Cognition and Computation*, *15*, 246–284. https://doi.org/10.1080/13875868.2015.1059432

Garlandini, S., & Fabrikant, S. I. (2009). Evaluating the Effectiveness and Efficiency of Visual Variables for Geographic Information Visualization. In K. S. Hornsby, C. Claramunt, M. Denis, & G. Ligozat (Eds.), *Spatial Information Theory* (pp. 195–211). Springer. https://doi.org/10.1007/978-3-642-03832-7_12

Gehrke, L., Iversen, J. R., Makeig, S., & Gramann, K. (2018). The invisible maze task (IMT): Interactive exploration of sparse virtual environments to investigate action-driven formation of spatial representations. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11034 LNAI*, 293–310. https://doi.org/10.1007/978-3-319-96385-3_20

Gelman, A. (2006). Multilevel (hierarchical) modeling: What It can and cannot do. *Technometrics*, *48*(3), 432–435. https://doi.org/10.1198/004017005000000661

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human–computer interaction. *Theoretical Issues in Ergonomics Science*, *4*(1–2), 113–131. https://doi.org/10.1080/14639220210159717

Ghani, U., Signal, N., Niazi, I. K., & Taylor, D. (2020). ERP based measures of cognitive workload: A review. *Neuroscience & Biobehavioral Reviews*, *118*, 18–26. https://doi.org/10.1016/j.neubiorev.2020.07.020

Gladwin, T. E., & De Jong, R. (2005). Bursts of occipital theta and alpha amplitude preceding alternation and repetition trials in a task-switching experiment. *Biological Psychology*, *68*(3), 309–329. https://doi.org/10.1016/J.BIOPSYCHO.2004.06.004

Göbel, F., Kiefer, P., & Raubal, M. (2019). FeaturEyeTrack: Automatic matching of eye tracking data with map features on interactive maps. *GeoInformatica*, *23*(4), 663–687. https://doi.org/10.1007/s10707-019-00344-3

Gramann, K. (2013). Embodiment of spatial reference frames and individual differences in reference frame proclivity. *Spatial Cognition and Computation*, *13*, 1–25. https://doi.org/10.1080/13875868.2011.589038

Gramann, K., Hohlefeld, F. U., Gehrke, L., & Klug, M. (2021). Human cortical dynamics during full-body heading changes. *Scientific Reports 2021 11:1*, *11*(1), 1–12. https://doi.org/10.1038/s41598-021-97749-8

Gramann, K., Onton, J., Riccobon, D., Mueller, H. J., Bardins, S., & Makeig, S. (2010). Human brain dynamics accompanying use of egocentric and allocentric reference frames during navigation. *Journal of Cognitive Neuroscience*, *22*(12), 2836–2849. https://doi.org/10.1162/jocn.2009.21369

Gras, D., Gyselinck, V., Perrussel, M., Orriols, E., & Piolino, P. (2013). The role of working memory components and visuospatial abilities in route learning within a virtual environment. *Journal of Cognitive Psychology*, *25*(1), 38–50. https://doi.org/10.1080/20445911.2012.739154

Handy, T. C., Soltani, M., & Mangun, G. R. (2001). Perceptual load and visuocortical processing: Event-related potentials reveal sensory-level selection. *Psychological Science*, *12*(3), 213–218. https://doi.org/10.1111/1467-9280.00338

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In P. A. Hancock & N. Meshkati (Eds.), *Advances in Psychology* (Vol. 52, pp. 139–183). North-Holland. https://doi.org/10.1016/S0166-4115(08)62386-9

Hartshorne, J. K., & Germine, L. T. (2015). When Does Cognitive Functioning Peak? The Asynchronous Rise and Fall of Different Cognitive Abilities Across the Life Span. *Psychological Science*, *26*(4), 433–443. https://doi.org/10.1177/0956797614567339

Hegarty, M., Richardson, A. E., Montello, D. R., Lovelace, K., & Subbiah, I. (2002). Development of a self-report measure of environmental spatial ability. *Intelligence*, *30*(5), 425–447. https://doi.org/10.1016/S0160-2896(02)00116-2

Hegarty, M., & Waller, D. (2004). A dissociation between mental rotation and perspective-taking spatial abilities. *Intelligence*, *32*(2), 175–191. https://doi.org/10.1016/j.intell.2003.12.001

Heinze, H. J., Luck, S. J., Mangun, G. R., & Hillyard, S. A. (1990). Visual event-related potentials index focused attention within bilateral stimulus arrays. I. Evidence for early selection. *Electroencephalography and Clinical Neurophysiology*, *75*(6), 511–527. https://doi.org/10.1016/0013-4694(90)90138-a

Hillyard, S. A., & Anllo-Vento, L. (1998). Event-related brain potentials in the study of visual selective attention. *Proceedings of the National Academy of Sciences of the United States of America*, *95*(3), 781–787. https://doi.org/10.1073/pnas.95.3.781

Hillyard, S. A., & Kutas, M. (1983). Electrophysiology of cognitive processing. *Annual Review of Psychology*, *34*, 33–61. https://doi.org/10.1146/annurev.ps.34.020183.000341

Hillyard, S., & Picton, T. (2011). Electrophysiology of Cognition. In *Handbook of Physiology,*. https://doi.org/10.1002/cphy.cp010513

Huang, H., Schmidt, M., & Gartner, G. (2012). Spatial Knowledge Acquisition with Mobile Maps, Augmented Reality and Voice in the Context of GPS-based Pedestrian Navigation: Results from a Field Test. *Cartography and Geographic Information Science*, *39*(2), 107–116. https://doi.org/10.1559/15230406392107

Hudspeth, W. J., & Pribram, K. H. (1990). Stages of brain and cognitive maturation. *Journal of Educational Psychology*, *82*, 881–884. https://doi.org/10.1037/0022-0663.82.4.881

Huffman, D. J., & Ekstrom, A. D. (2018). Which way is the bookstore? A closer look at the judgments of relative directions task. *Spatial Cognition and Computation*. https://doi.org/10.1080/13875868.2018.1531869

Hund, A. M. (2016). Visuospatial working memory facilitates indoor wayfinding and direction giving. *Journal of Environmental Psychology*, *45*, 233–238. https://doi.org/10.1016/j.jenvp.2016.01.008

Ishikawa, T. (2019). Satellite Navigation and Geospatial Awareness: Long-Term Effects of Using Navigation Tools on Wayfinding and Spatial Orientation. *The Professional Geographer*, *71*(2), 197–209. https://doi.org/10.1080/00330124.2018.1479970

Ishikawa, T. (2020). *Human Spatial Cognition and Experience: Mind in the World, World in the Mind*. Routledge.

Ishikawa, T., Fujiwara, H., Imai, O., & Okabe, A. (2008). Wayfinding with a GPS-based mobile navigation system: A comparison with maps and direct experience. *Journal of Environmental Psychology*, *28*(1), 74–82. https://doi.org/10.1016/j.jenvp.2007.09.002

Ishikawa, T., & Montello, D. R. (2006). Spatial knowledge acquisition from direct experience in the environment: Individual differences in the development of metric knowledge and the integration of separately learned places. *Cognitive Psychology*, *52*(2), 93–129. https://doi.org/10.1016/j.cogpsych.2005.08.003

Isreal, J. B., Wickens, C. D., Chesney, G. L., & Donchin, E. (1980). The event-related brain potential as an index of display-monitoring workload. *Human Factors*, *22*(2), 211–224. https://doi.org/10.1177/001872088002200210

Jansen-Osmann, P., & Fuchs, P. (2006). Wayfinding Behavior and Spatial Knowledge of Adults and Children in a Virtual Environment. *Experimental Psychology*, *53*(3), 171–181. https://doi.org/10.1027/1618-3169.53.3.171

Jansen-Osmann, P., & Wiedenbauer, G. (2004). The representation of landmarks and routes in children and adults: A study in a virtual environment. *Journal of Environmental Psychology*, *24*(3), 347–357. https://doi.org/10.1016/j.jenvp.2004.08.003

Jensen, O., & Mazaheri, A. (2010). Shaping Functional Architecture by Oscillatory Alpha Activity: Gating by Inhibition. *Frontiers in Human Neuroscience*, *4*. https://www.frontiersin.org/article/10.3389/fnhum.2010.00186

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. *European Journal of Neuroscience*, *15*(8), 1395–1399. https://doi.org/10.1046/j.1460-9568.2002.01975.x

Jeung, S., Hilton, C., Berg, T., Gehrke, L., & Gramann, K. (2022). Virtual Reality for Spatial Navigation. *Current Topics in Behavioral Neurosciences*. https://doi.org/10.1007/7854_2022_403

Kalantari, S., Tripathi, V., Kan, J., Rounds, J. D., Mostafavi, A., Snell, R., & Cruz-Garza, J. G. (2022). Evaluating the impacts of color, graphics, and architectural features on wayfinding in healthcare settings using EEG data and virtual response testing. *Journal of Environmental Psychology*, *79*, 101744. https://doi.org/10.1016/j.jenvp.2021.101744

Keil, J., Edler, D., Kuchinke, L., & Dickmann, F. (2020). Effects of visual map complexity on the attentional processing of landmarks. *PloS One*, *15*(3), e0229575. https://doi.org/10.1371/journal.pone.0229575

Kim, K., & Bock, O. (2021). Acquisition of landmark, route, and survey knowledge in a wayfinding task: In stages or in parallel? *Psychological Research*, *85*(5), 2098–2106. https://doi.org/10.1007/S00426-020-01384-3/FIGURES/5

Klatzky, R. L. (1998). Allocentric and Egocentric Spatial Representations: Definitions, Distinctions, and Interconnections. In C. Freksa, C. Habel, & K. F. Wender (Eds.), *Spatial Cognition: An Interdisciplinary Approach to Representing and Processing Spatial Knowledge* (pp. 1–17). Springer. https://doi.org/10.1007/3-540-69342-4_1

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews*, *29*(2–3), 169–195. https://doi.org/10.1016/S0165-0173(98)00056-3

Klimesch, W., Doppelmayr, M., Russegger, H., Pachinger, T., & Schwaiger, J. (1998). Induced alpha band power changes in the human EEG and attention. *Neuroscience Letters*, *244*(2), 73–76. https://doi.org/10.1016/S0304-3940(98)00122-0

Klug, M., & Gramann, K. (2021). Identifying key factors for improving ICA-based decomposition of EEG data in mobile and stationary experiments. *European Journal of Neuroscience*, *54*(12), 8406–8420. https://doi.org/10.1111/ejn.14992

Klug, M., Jeung, S., Wunderlich, A., Gehrke, L., Protzak, J., Djebbara, Z., Argubi-Wollesen, A., Wollesen, B., & Gramann, K. (2022). The BeMoBIL Pipeline for automated analyses of multimodal mobile brain and body imaging data. *BioRxiv*, 2022.09.29.510051. https://doi.org/10.1101/2022.09.29.510051

Klug, M., & Kloosterman, N. A. (2022). Zapline-plus: A Zapline extension for automatic and adaptive removal of frequency-specific noise artifacts in M/EEG. *Human Brain Mapping*. https://doi.org/10.1002/HBM.25832

Knight, M. J., & Tlauka, M. (2018). Map learning and working memory: Multimodal learning strategies. *Quarterly Journal of Experimental Psychology (2006)*, *71*(6), 1405–1418. https://doi.org/10.1080/17470218.2017.1326954

Kok, A. (2001). On the utility of P3 amplitude as a measure of processing capacity. *Psychophysiology*, *38*(3), 557–577. https://doi.org/10.1017/S0048577201990559

Krause, C. M., Sillanmäki, L., Koivisto, M., Saarela, C., Häggqvist, A., Laine, M., & Hämäläinen, H. (2000). The effects of memory load on event-related EEG desynchronization and synchronization. *Clinical Neurophysiology*, *111*(11), 2071–2078. https://doi.org/10.1016/S1388-2457(00)00429-6

Krejtz, K., Duchowski, A. T., Niedzielska, A., Biele, C., & Krejtz, I. (2018). Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze. *PLOS ONE*, *13*(9), e0203629. https://doi.org/10.1371/journal.pone.0203629

Kuipers, B. (1978). Modeling Spatial Knowledge*. *Cognitive Science*, *2*(2), 129–153. https://doi.org/10.1207/s15516709cog0202_3

Kunz, L., Schröder, T. N., Lee, H., Montag, C., Lachmann, B., Sariyska, R., Reuter, M., Stirnberg, R., Stöcker, T., Messing-Floeter, P. C., Fell, J., Doeller, C. F., & Axmacher, N. (2015). Reduced grid-cell-like representations in adults at genetic risk for Alzheimer's disease. *Science (New York, N.Y.)*, *350*(6259), 430–433. https://doi.org/10.1126/science.aac8128

Labate, E., Pazzaglia, F., & Hegarty, M. (2014). What working memory subcomponents are needed in the acquisition of survey knowledge? Evidence from direction estimation and shortcut tasks. *Journal of Environmental Psychology*, *37*, 73–79. https://doi.org/10.1016/J.JENVP.2013.11.007

Lee, A. S., Blankson, B. K., Manza, P., O'Rawe, J. F., Evinger, C., & Leung, H.-C. (2018). Spontaneous but not voluntary eye blinks during spatial working memory are 1 associated with successful performance 2 3. In *BioRxiv preprint*. https://doi.org/10.1101/345306

Li, R. (2020). Spatial Learning in Smart Applications: Enhancing Spatial Awareness through Visualized Off-Screen Landmarks on Mobile Devices. *Annals of the American Association of Geographers*, *110*(2), 421–433. https://doi.org/10.1080/24694452.2019.1670611

Liao, H., Dong, W., Peng, C., & Liu, H. (2017). Exploring differences of visual attention in pedestrian navigation when using 2D maps and 3D geo-browsers. *Cartography and Geographic Information Science*, *44*(6), 474–490. https://doi.org/10.1080/15230406.2016.1174886

Ligonnière, V., Gyselinck, V., Lhuillier, S., Mostafavi, M. A., & Dommes, A. (2021). How does the visual and cognitive saliency of landmarks improve construction of spatial representations in younger and older adults? *Spatial Cognition and Computation*, *21*(4), 320–345. https://doi.org/10.1080/13875868.2021.1992410

Liu, J., Singh, A. K., & Lin, C.-T. (2022). Using virtual global landmark to improve incidental spatial learning. *Scientific Reports 2022 12:1*, *12*(1), 1–14. https://doi.org/10.1038/s41598-022-10855-z

Liu, S., Shen, J., Li, Y., Wang, J., Wang, J., Xu, J., Wang, Q., & Chen, R. (2021). EEG Power Spectral Analysis of Abnormal Cortical Activations During REM/NREM Sleep in Obstructive Sleep Apnea. *Frontiers in Neurology*, *12*. https://www.frontiersin.org/articles/10.3389/fneur.2021.643855

Liu, T. X., Bednar, J., Chen, Y., & Page, S. (2019). Directional behavioral spillover and cognitive load effects in multiple repeated games. *Experimental Economics*, *22*(3), 705–734. https://doi.org/10.1007/s10683-018-9570-7

Lobben, A. K. (2004). Tasks, Strategies, and Cognitive Processes Associated With Navigational Map Reading: A Review Perspective. *The Professional Geographer*, *56*(2), 270–281. https://doi.org/10.1111/j.0033-0124.2004.05602010.x

Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn't). *Psychophysiology*, *54*(1), 146–157. https://doi.org/10.1111/psyp.12639

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–284. https://doi.org/10.1038/36846

Lynch, K. A. (1960). *The Image of the City*. The MIT Press.

Maguire, E. A., Woollett, K., & Spiers, H. J. (2006). London taxi drivers and bus drivers: A structural MRI and neuropsychological analysis. *Hippocampus*, *16*(12), 1091–1101. https://doi.org/10.1002/hipo.20233

Makeig, S., Bell, A., Jung, T.-P., & Sejnowski, T. J. (1995). Independent Component Analysis of Electroencephalographic Data. In D. Touretzky, M. C. Mozer, & M. Hasselmo (Eds.), *Advances in Neural Information Processing Systems* (Vol. 8). MIT Press. https://proceedings.neurips.cc/paper/1995/file/754dda4b1ba34c6fa89716b85d68532b-Paper.pdf

Maurer, U., Brem, S., Liechti, M., Maurizio, S., Michels, L., & Brandeis, D. (2015). Frontal Midline Theta Reflects Individual Task Performance in a Working Memory Task. *Brain Topography*, *28*(1), 127–134. https://doi.org/10.1007/s10548-014-0361-y

McDermott, T. J., Wiesman, A. I., Proskovec, A. L., Heinrichs-Graham, E., & Wilson, T. W. (2017). Spatiotemporal oscillatory dynamics of visual selective attention during a flanker task. *NeuroImage*, *156*, 277–285. https://doi.org/10.1016/j.neuroimage.2017.05.014

McKinlay, R. (2016). Technology: Use or lose our navigation skills. *Nature*, *531*(7596), Article 7596. https://doi.org/10.1038/531573a

Meneghetti, C., Miola, L., Toffalini, E., Pastore, M., & Pazzaglia, F. (2021). Learning from navigation, and tasks assessing its accuracy: The role of visuospatial abilities and wayfinding inclinations. *Journal of Environmental Psychology*, *75*. https://doi.org/10.1016/j.jenvp.2021.101614

Miola, L., Meneghetti, C., Gyselinck, V., Curcio, F. G., & Pazzaglia, F. (2021). The influence of environmental context on spatial learning. Openness of the environment and spatial mental representations in the city of Venice. *Journal of Environmental Psychology*, *76*, 101629. https://doi.org/10.1016/j.jenvp.2021.101629

Montello. (2011). A new framework for understanding the acquisition of spatial knowledge in large-scale environments. In *Biomedical Materials* (Vol. 6). https://doi.org/10.1088/1748-6041/6/2/025001

Montello, D. R. (2002). Cognitive Map-Design Research in the Twentieth Century: Theoretical and Empirical Approaches. *Cartography and Geographic Information Science*, *29*(3), 283–304. https://doi.org/10.1559/152304002782008503

Montello, Daniel. R. (2005). Navigation. In *The Cambridge Handbook of Visuospatial Thinking* (pp. 257–294). Cambridge University Press. https://doi.org/10.1017/cbo9780511610448.008

Moran, R. J., Campo, P., Maestu, F., Reilly, R. B., Dolan, R. J., & Strange, B. A. (2010). Peak Frequency in the Theta and Alpha Bands Correlates with Human Working Memory Capacity. *Frontiers in Human Neuroscience*, *4*. https://doi.org/10.3389/FNHUM.2010.00200

Münzer, S., & Hölscher, C. (2011). Entwicklung und Validierung eines Fragebogens zu räumlichen Strategien. *Diagnostica*, *57*(3), 111–125. https://doi.org/10.1026/0012-1924/a000040

Münzer, S., Lörch, L., & Frankenstein, J. (2020). Wayfinding and acquisition of spatial knowledge with navigation assistance. *Journal of Experimental Psychology: Applied*, *26*(1), 73–88. https://doi.org/10.1037/xap0000237

Münzer, S., Zimmer, H. D., & Baus, J. (2012). Navigation assistance: A trade-off between wayfinding support and configural learning support. *Journal of Experimental Psychology: Applied*, *18*(1), 18–37. https://doi.org/10.1037/a0026553

Murakami, H. (2011). *1Q84*. Random House. https://scholar.google.com/scholar_lookup?title=1Q84&author=H.%20Murakami&publication_year=2009#d=gs_cit&t=1658739290571&u=%2Fscholar%3Fq%3Dinfo%3Ah6ssIRyA7DEJ%3Ascholar.google.com%2F%26output%3Dcite%26scirp%3D0%26hl%3Den

Näätänen, R. (1992). Attention and brain function. *Lawrence Erlbaum Associates, Inc.* https://psycnet.apa.org/record/1992-98140-000

Nelli, S., Itthipuripat, S., Srinivasan, R., & Serences, J. T. (2017). Fluctuations in instantaneous frequency predict alpha amplitude during visual perception. *Nature Communications 2017 8:1*, *8*(1), 1–12. https://doi.org/10.1038/s41467-017-02176-x

Nishiyori, R., Xiao, R., Vanderbilt, D., & Smith, B. A. (2021). Electroencephalography measures of relative power and coherence as reaching skill emerges in infants born preterm. *Scientific Reports 2021 11:1*, *11*(1), 1–14. https://doi.org/10.1038/s41598-021-82329-7

Nori, R., Grandicelli, S., & Giusberti, F. (2009). Individual differences in visuo-spatial working memory and real-world wayfinding. *Swiss Journal of Psychology*, *68*(1), 7–16. https://doi.org/10.1024/1421-0185.68.1.7

O'Connor, M. R. (2019). *Wayfinding: The Science and Mystery of How Humans Navigate the World*. St. Martin's Press.

O'Keefe, J., & Nadel, L. (1978). *The Hippocampus as a Cognitive Map*. Oxford University Press. http://www.cognitivemap.net/

O'Mara, S. (2020). *In Praise of Walking: A New Scientific Exploration*. W. W. Norton & Company.

Onton, J., Delorme, A., & Makeig, S. (2005). Frontal midline EEG dynamics during working memory. *NeuroImage*, *27*(2), 341–356. https://doi.org/10.1016/j.neuroimage.2005.04.014

Oostenveld, R., & Oostendorp, T. F. (2002). Validating the boundary element method for forward and inverse EEG computations in the presence of a hole in the skull. *Human Brain Mapping*, *17*(3), 179–192. https://doi.org/10.1002/HBM.10061

Orsini, A., Grossi, D., Capitani, E., Laiacona, M., Papagno, C., & Vallar, G. (1987). Verbal and spatial immediate memory span: Normative data from 1355 adults and 1112 children. *The Italian Journal of Neurological Sciences 1987 8:6*, *8*(6), 537–548. https://doi.org/10.1007/BF02333660

Palmer, J., Kreutz-Delgado, K., & Makeig, S. (2011). AMICA: An Adaptive Mixture of Independent Component Analyzers with Shared Components. *Swartz Center for Computatonal Neursoscience, University of California San Diego, Techical Report*.

Palva, S., & Palva, J. M. (2007). New vistas for alpha-frequency band oscillations. *Trends in Neurosciences*, *30*(4), 150–158. https://doi.org/10.1016/j.tins.2007.02.001

Parks, T. E. (1966). Signal-detectability theory of recognition-memory performance. *Psychological Review*, *73*(1), 44–58. https://doi.org/10.1037/h0022662

Parush, A., Ahuvia, S., & Erev, I. (2007). Degradation in Spatial Knowledge Acquisition When Using Automatic Navigation Systems. *International Conference on Spatial Information Theory*, 238–254. https://doi.org/10.1007/978-3-540-74788-8_15

Pastel, S., Bürger, D., Chen, C. H., Petri, K., & Witte, K. (2022). Comparison of spatial orientation skill between real and virtual environment. *Virtual Reality*, *26*(1), 91–104. https://doi.org/10.1007/s10055-021-00539-w

Pew Research. (2011). *28% of American adults use mobile and social location-based services*. https://www.pewresearch.org/internet/2011/09/06/28-of-american-adults-use-mobile-and-social-location-based-services/

Pew Research. (2015). *U.S. Smartphone Use in 2015*.

Pew Research. (2021). *Mobile Fact Sheet*.

Pfurtscheller, G., & Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: Basic principles. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *110*(11), 1842–1857. https://doi.org/10.1016/s1388-2457(99)00141-8

Pfurtscheller, G., Stancák, A., & Neuper, Ch. (1996). Event-related synchronization (ERS) in the alpha band — an electrophysiological correlate of cortical idling: A review. *International Journal of Psychophysiology*, *24*(1), 39–46. https://doi.org/10.1016/S0167-8760(96)00066-9

Piaget, J., & Inhelder, B. (1967). *The child's conception of space*. W. W. Norton & Company. https://www.abebooks.com/9780393004083/Childs-Conception-Space-Norton-Library-0393004082/plp

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website HHS Public Access. *Neuroimage*, *198*, 181–197. https://doi.org/10.1016/j.neuroimage.2019.05.026

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148. https://doi.org/10.1016/J.CLINPH.2007.04.019

Puma, S., Matton, N., Paubel, P. V., Raufaste, É., & El-Yagoubi, R. (2018). Using theta and alpha band power to assess cognitive workload in multitasking environments. *International Journal of Psychophysiology*, *123*, 111–120. https://doi.org/10.1016/J.IJPSYCHO.2017.10.004

Ratcliffe, O., Shapiro, K., & Staresina, B. P. (2022). Fronto-medial theta coordinates posterior maintenance of working memory content. *Current Biology*. https://doi.org/10.1016/j.cub.2022.03.045

Raubal, M., & Winter, S. (2002). Enriching wayfinding instructions with local landmarks. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *2478*, 243–259. https://doi.org/10.1007/3-540-45799-2_17

Richter, K. F., & Winter, S. (2014). Landmarks: Giscience for intelligent services. In *Landmarks: Giscience for Intelligent Services*. Springer International Publishing. https://doi.org/10.1007/978-3-319-05732-3

Ruginski, I., Giudice, N., Creem-Regehr, S., & Ishikawa, T. (2022). Designing mobile spatial navigation systems from the user's perspective: An interdisciplinary review. *Spatial Cognition & Computation*, *22*(1–2), 1–29. https://doi.org/10.1080/13875868.2022.2053382

Ruginski, I. T., Creem-Regehr, S. H., Stefanucci, J. K., & Cashdan, E. (2019). GPS-use negatively affects environmental learning through spatial transformation abilities. *Journal of Environmental Psychology*, *64*, 12–20. https://doi.org/10.1016/j.jenvp.2019.05.001

Sahar, T., Sidi, Y., & Makovski, T. (2020). A Metacognitive Perspective of Visual Working Memory With Rich Complex Objects. *Frontiers in Psychology*, *11*. https://www.frontiersin.org/articles/10.3389/fpsyg.2020.00179

Sanchez-Vives, M. V., & Slater, M. (2005). From presence to consciousness through virtual reality. *Nature Reviews Neuroscience*, *6*(4), Article 4. https://doi.org/10.1038/nrn1651

Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory: A possible function of EEG theta oscillations. *Neuroscience and Biobehavioral Reviews*, *34*(7), 1015–1022. https://doi.org/10.1016/j.neubiorev.2009.12.006

Sauseng, P., Klimesch, W., Stadler, W., Schabus, M., Doppelmayr, M., Hanslmayr, S., Gruber, W. R., & Birbaumer, N. (2005). A shift of visual spatial attention is selectively associated with human EEG alpha activity. *European Journal of Neuroscience*, *22*(11), 2917–2926. https://doi.org/10.1111/J.1460-9568.2005.04482.X

Savino, G.-L., Meyer, L., Schade, E. E. S., Tenbrink, T., & Schöning, J. (2020). Point Me In the Right Direction: Understanding User Behaviour with As-The-Crow-Flies Navigation. *22nd International Conference on Human-Computer Interaction with Mobile Devices and Services*, 1–11. https://doi.org/10.1145/3379503.3403539

Savino, G.-L., Sturdee, M., Rundé, S., Lohmeier, C., Hecht, B., Prandi, C., Nunes, N. J., & Schöning, J. (2021). MapRecorder: Analysing real-world usage of mobile map applications. *Behaviour & Information Technology*, *40*(7), 646–662. https://doi.org/10.1080/0144929X.2020.1714733

Scharinger, C., Soutschek, A., Schubert, T., & Gerjets, P. (2017). Comparison of the working memory load in N-back and working memory span tasks by means of EEG frequency band power and P300 amplitude. *Frontiers in Human Neuroscience*, *11*, 6. https://doi.org/10.3389/fnhum.2017.00006

Schøyen Collection. (n.d.). *CYLCON (YURDA), POSSIBLY WITH MAP OF DARLING RIVER*. Retrieved April 24, 2022, from https://www.schoyencollection.com/24-smaller-collections/maps/cylcon-darling-river-ms-5087-36

Shors, T. J., Anderson, L., Curlik, D. M., & Nokia, S. (2012). Use it or lose it: How neurogenesis keeps the brain fit for learning. *Behavioural Brain Research*, *227*(2), 450–458. https://doi.org/10.1016/j.bbr.2011.04.023

Siegel, A. W., & White, S. H. (1975). The Development of Spatial Representations of Large-Scale Environments. In H. W. Reese (Ed.), *Advances in Child Development and Behavior* (Vol. 10, pp. 9–55). JAI. https://doi.org/10.1016/S0065-2407(08)60007-5

Siegle, G. J., Ichikawa, N., & Steinhauer, S. (2008). Blink before and after you think: Blinks occur prior to and following cognitive load indexed by pupillary responses. *Psychophysiology*, *45*(5), 679–687. https://doi.org/10.1111/j.1469-8986.2008.00681.x

Smith, M. E., Gevins, A., Brown, H., Karnik, A., & Du, R. (2001). Monitoring task loading with multivariate EEG measures during complex forms of human-computer interaction. *Human Factors*, *43*(3), 366–380. https://doi.org/10.1518/001872001775898287

Sorrows, M. E., & Hirtle, S. C. (1999). The Nature of Landmarks for Real and Electronic Spaces. In C. Freksa & D. M. Mark (Eds.), *Spatial Information Theory. Cognitive* *and Computational Foundations of Geographic Information Science* (pp. 37–50). Springer. https://doi.org/10.1007/3-540-48384-5_3

Spiers, H. J., Coutrot, A., & Hornberger, M. (2023). Explaining World-Wide Variation in Navigation Ability from Millions of People: Citizen Science Project Sea Hero Quest. *Topics in Cognitive Science*, *15*(1), 120–138. https://doi.org/10.1111/tops.12590

Stankiewicz, B. J., & Kalia, A. A. (2007). Acquisition of Structural Versus Object Landmark Knowledge. *Journal of Experimental Psychology: Human Perception and Performance*, *33*(2), 378–390. https://doi.org/10.1037/0096-1523.33.2.378

Stea, D. (Ed.). (1973). Cognitive Maps and Spatial Behavior: Process and Products. In *Image and Environment*. Routledge.

Stern, J. A., Walrath, L. C., & Goldstein, R. (1984). The endogenous eyeblink. *Psychophysiology*, *21*(1), 22–33. https://doi.org/10.1111/j.1469-8986.1984.tb02312.x

Stevens, C. A., & Carlson, R. A. (2019). Is simpler always better? Effects of perceptual detail and viewpoint on spatial cognition and metacognition. *The American Journal of Psychology*, *132*, 293–301. https://doi.org/10.5406/amerjpsyc.132.3.0293

Stipacek, A., Grabner, R. H., Neuper, C., Fink, A., & Neubauer, A. C. (2003). Sensitivity of human EEG alpha band desynchronization to different working memory components and increasing levels of memory load. *Neuroscience Letters*, *353*(3), 193–196. https://doi.org/10.1016/J.NEULET.2003.09.044

Stites, M. C., Matzen, L. E., & Gastelum, Z. N. (2020). Where are we going and where have we been? Examining the effects of maps on spatial learning in an indoor guided navigation task. *Cognitive Research: Principles and Implications*, *5*(1), 13. https://doi.org/10.1186/s41235-020-00213-w

Sugimoto, F., Kimura, M., & Takeda, Y. (2022). Investigation of the optimal time interval between task-irrelevant auditory probes for evaluating mental workload in the shortest possible time. *International Journal of Psychophysiology*, *177*, 103–110. https://doi.org/10.1016/j.ijpsycho.2022.04.013

Sugimoto, M., Kusumi, T., Nagata, N., & Ishikawa, T. (2021). Online mobile map effect: How smartphone map use impairs spatial memory. *Spatial Cognition and Computation*. https://doi.org/10.1080/13875868.2021.1969401

Sweller, J. (1988). Cognitive Load During Problem Solving: Effects on Learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J., van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive Architecture and Instructional Design. *Educational Psychology Review*, *10*(3), 251–296. https://doi.org/10.1023/A:1022193728205

Takeda, Y., Okuma, T., Kimura, M., Kurata, T., Takenaka, T., & Iwaki, S. (2014). Electrophysiological measurement of interest during walking in a simulated environment. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *93*(3), 363–370. https://doi.org/10.1016/j.ijpsycho.2014.05.012

Teimouri, F., & Richter, K. F. (2022). Abstracting routes to their route-defining locations. *Computers, Environment and Urban Systems*, *91*. https://doi.org/10.1016/j.compenvurbsys.2021.101732

Thorndyke, P., & Hayes-Roth, B. (1982). Differences in Spatial Knowledge Acquired and Navigation from Maps. *Cognitive Psychology*, *589*, 560–589. https://doi.org/10.1016/0010-0285(82)90019-6

Toda, T., Parylak, S. L., Linker, S. B., & Gage, F. H. (2019). The role of adult hippocampal neurogenesis in brain health and disease. *Molecular Psychiatry*, *24*(1), Article 1. https://doi.org/10.1038/s41380-018-0036-2

Tolman, E. C. (1948). Cognitive maps in rats and men. *Psychological Review*, *55*, 189–208. https://doi.org/10.1037/h0061626

Tonucci, F., & Rissotto, A. (2001). Why do we need children's participation? The importance of children's participation in changing the city. *Journal of Community & Applied Social Psychology*, *11*(6), 407–419. https://doi.org/10.1002/casp.641

Trojano, L., Chiacchio, L., De Luca, G., Fragassi, N. A., & Grossi, D. (1994). Effect of testing procedure on Corsi's block-tapping task in normal subjects and Alzheimer-type dementia. *Perceptual and Motor Skills*, *78*(3 Pt 1), 859–863. https://doi.org/10.1177/003151259407800336

Uttal, D. H., & Cohen, C. A. (2012). Spatial Thinking and STEM Education. When, Why, and How? In *Psychology of Learning and Motivation—Advances in Research and Theory* (Vol. 57, pp. 147–181). https://doi.org/10.1016/B978-0-12-394293-7.00004-2

Valtchanov, D., & Ellard, C. G. (2015). Cognitive and affective responses to natural scenes: Effects of low level visual properties on preference, cognitive load and eye-movements. *Journal of Environmental Psychology*, *43*, 184–195. https://doi.org/10.1016/j.jenvp.2015.07.001

van der Ham, I. J. M., Claessen, M. H. G., Evers, A. W. M., & van der Kuil, M. N. A. (2020). Large-scale assessment of human navigation ability across the lifespan. *Scientific Reports*, *10*(1), Article 1. https://doi.org/10.1038/s41598-020-60302-0

Van der Stelt, O., Geesken, R., Gunning, W. B., Snel, J., & Kok, A. (1998). P3 scalp topography to target and novel visual stimuli in children of alcoholics. *Alcohol (Fayetteville, N.Y.)*, *15*(2), 119–136. https://doi.org/10.1016/s0741-8329(97)00106-7

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions and objects in visual working memory. *Journal of Experimental Psychology. Human Perception and Performance*, *27*(1), 92–114. https://doi.org/10.1037//0096-1523.27.1.92

Wang, Y. K., Jung, T. P., & Lin, C. T. (2018). Theta and alpha oscillations in attentional interaction during distracted driving. *Frontiers in Behavioral Neuroscience*, *12*, 3. https://doi.org/10.3389/fnbeh.2018.00003

Wang, Y., Sokhadze, E. M., El-Baz, A. S., Li, X., Sears, L., Casanova, M. F., & Tasman, A. (2015). Relative Power of Specific EEG Bands and Their Ratios during Neurofeedback Training in Children with Autism Spectrum Disorder. *Frontiers in Human Neuroscience*, *9*(JAN2016). https://doi.org/10.3389/FNHUM.2015.00723

Wascher, E., Arnau, S., Gutberlet, M., Chuang, L. L., Rinkenauer, G., & Reiser, J. E. (2022). Visual Demands of Walking Are Reflected in Eye-Blink-Evoked EEG-Activity. *Applied Sciences*, *12*(13), Article 13. https://doi.org/10.3390/app12136614

Wascher, E., Heppner, H., & Hoffmann, S. (2014). Towards the measurement of event-related EEG activity in real-life working environments. *International Journal of Psychophysiology*, *91*(1), 3–9. https://doi.org/10.1016/j.ijpsycho.2013.10.006

Wascher, E., Heppner, H., Kobald, S. O., Arnau, S., Getzmann, S., & Möckel, T. (2016). Age-sensitive effects of enduring work with alternating cognitive and physical load. A study applying mobile EEG in a real life working scenario. *Frontiers in Human Neuroscience*, *9*(JAN2016). https://doi.org/10.3389/fnhum.2015.00711

Watter, S., Geffen, G. M., & Geffen, L. B. (2001). The n-back as a dual-task: P300 morphology under divided attention. *Psychophysiology*, *38*(6), 998–1003. https://doi.org/10.1111/1469-8986.3860998

Wei, H., & Zhou, R. (2020). High working memory load impairs selective attention: EEG signatures. *Psychophysiology*, *57*(11), e13643. https://doi.org/10.1111/psyp.13643

Weisberg, S. M., & Newcombe, N. S. (2016). How do (some) people make a cognitive map? Routes, places, and working memory. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *42*(5), 768–785. https://doi.org/10.1037/xlm0000200

Weisberg, S. M., & Newcombe, N. S. (2018). Cognitive Maps: Some People Make Them, Some People Struggle. *Current Directions in Psychological Science*, *27*(4), 220–226. https://doi.org/10.1177/0963721417744521

Weisberg, S. M., Schinazi, V. R., Newcombe, N. S., Shipley, T. F., & Epstein, R. A. (2014). Variations in cognitive maps: Understanding individual differences in navigation. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *40*(3), 669–682. https://doi.org/10.1037/a0035261

Wenig, N., Wenig, D., Ernst, S., Malaka, R., Hecht, B., & Schöning, J. (2017). Pharos: Improving navigation instructions on smartwatches by including global landmarks. *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services, MobileHCI 2017*. https://doi.org/10.1145/3098279.3098529

White, D. J., Congedo, M., Ciorciari, J., & Silberstein, R. B. (2012). Brain Oscillatory Activity during Spatial Navigation:Theta and Gamma Activity Link Medial Temporal and

Parietal Regions. *Journal of Cognitive Neuroscience*, *24*(3), 686–697. https://doi.org/10.1162/jocn_a_00098

Wiener, J. M., Büchner, S. J., & Hölscher, C. (2009). Taxonomy of Human Wayfinding Tasks: A Knowledge-Based Approach. *Spatial Cognition & Computation*, *9*(2), 152–165. https://doi.org/10.1080/13875860902906496

Wiener, J. M., & Pazzaglia, F. (2021). Ageing- and dementia-friendly design: Theory and evidence from cognitive psychology, neuropsychology and environmental psychology can contribute to design guidelines that minimise spatial disorientation. *Cognitive Processing*, *22*(4), 715–730. https://doi.org/10.1007/s10339-021-01031-8

Wolodtschenko, A., & Forner, T. (2007). *Prehistoric and early historic maps in Europe: Conception of Cd-Atlas*. *2*, 114–116.

Woodman, G. F. (2010). A Brief Introduction to the Use of Event-Related Potentials (ERPs) in Studies of Perception and Attention. *Attention, Perception & Psychophysics*, *72*(8), 10.3758/APP.72.8.2031. https://doi.org/10.3758/APP.72.8.2031

Wunderlich, A., & Gramann, K. (2020). Eye movement-related brain potentials during assisted navigation in real-world environments. *European Journal of Neuroscience*. https://doi.org/10.1111/ejn.15095

Wunderlich, A., & Gramann, K. (2021). Landmark-based navigation instructions improve incidental spatial knowledge acquisition in real-world environments. *Journal of Environmental Psychology*, *77*. https://doi.org/10.1016/j.jenvp.2021.101677

Yan, J. H., Thomas, J. R., & Downing, J. H. (1998). Locomotion Improves Children's Spatial Search: A Meta-Analytic Review. *Perceptual and Motor Skills*, *87*(1), 67–82. https://doi.org/10.2466/pms.1998.87.1.67

Yesiltepe, D., Conroy Dalton, R., & Ozbil Torun, A. (2021). Landmarks in wayfinding: A review of the existing literature. *Cognitive Processing*, *22*(3), 369–410. https://doi.org/10.1007/s10339-021-01012-x

Zhang, H., Zherdeva, K., & Ekstrom, A. D. (2014). Different "routes" to a cognitive map: Dissociable forms of spatial knowledge derived from route and cartographic map learning. *Memory & Cognition*, *42*(7), 1106. https://doi.org/10.3758/S13421-014-0418-X

Supplementary Materials

The following supplementary materials for the experiment and the analyses can be found on the open access Github page: https://github.com/BingjieCheng/PhDThesis.git

1. Experiment

    1.1 Information sheet & Consent form

    1.2 Santa Barbara Sense of Direction (SBSOD) questionnaire

    1.3 Perspective Taking/Spatial Orientation Test (PT/SOT)

    1.4 Corsi Block-Tapping Test (CBTT)

2. Analysis Scripts

    2.1 R script of linear mixed-effect models

    2.2 Matlab script of BeMobile preprocessing

    2.3 Matlab script of event-related potential (ERP) analysis

    2.4 Matlab script of power spectral analysis (PSA)

    2.5 Matlab script of blink-related ERP analysis

The 3D virtual cities can be found in the following SwitchDrive folder: https://drive.switch.ch/index.php/s/tlz0ljRn4KBGFzD

A Video clip that records the navigation experiment can be found in the following SwitchDrive folder: https://drive.switch.ch/index.php/s/VETOfWzKg2GBGqA