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Walk and learn: effects of human-centered navigation systems on pedestrians' navigation behavior

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Abstract: A city of the future is likely to be one where people, sensors, and the environment fuse together into one interconnected, dependent, and intelligent system - a smart city. Accordingly, navigation in a smart city will also change drastically, as intelligent navigation systems will autonomously guide people from one place to another. Using these automated systems, people will be able to navigate to their destination more efficiently, but these systems also appear to decrease cognitive development relevant to learning and memory in everyday activities. By relying more on a navigation system rather than relevant features in the environment, humans may lose the ability to acquire spatial knowledge that, amongst other things, ensures brain development. It is known that people develop these essential cognitive abilities for everyday situations when using analog maps. However, little is known about how analog and automated navigation assistance can be combined to ensure efficient navigation without losing the ability to acquire spatial knowledge. This thesis aims to understand the relationship between a human navigator and partly automated navigation systems in real-world environments, as most navigation experiments up until now have only assessed human behavior and spatial knowledge acquisition in virtual labs. In order to ensure that experiments are based around real-life situations, I have developed an experimental 'WALK-AND-LEARN' framework, which evaluates human navigation behavior and spatial knowledge acquisition in urban, real-world environments. The framework consists of an assisted route-following (incidental spatial knowledge acquisition) and an unassisted route-reversal (spatial knowledge recall) task. The framework allows pedestrians to use all their senses in-situ during both the learning and testing phases. This should account for the shortcomings of traditional setups, such as controlled lab experiments. Two experiments assessed pedestrian interactions with various navigation systems and with the environment traversed. I designed partly automated navigation systems by systematically analyzing cognitive processes between human-centered (a low level of automation) and system-centered (a high level of automation) navigation system designs. Data on navigation performance, interactions with the navigation system, and mobile eye-tracking recordings build the basis for the spatial analysis of pedestrian behavior in the real world. The methodology provides unique insights into the behavior of pedestrians using navigation systems in urban environments. The results show how human-centered navigation assistance can be designed to ensure a high level of navigation efficiency without losing the ability to acquire spatial knowledge. Specifically, the results show that a system that demands proactive human decision-making can assist navigators in incidentally acquiring spatial knowledge, while a system using context-dependent information does not. This thesis shows that participants who are tested in-situ can use all their senses to acquire and to recall spatial knowledge. In addition, and more importantly, this thesis also reveals the significance of the complexity of the traversed environment, such as traffic, in understanding pedestrian behavior and the acquisition of spatial knowledge in real-world navigation tasks. The analyses in this thesis have uncovered distinctive environment-dependent patterns of map interaction behavior, for example map rotations at turns, and gaze behavior, for example varying attention to the navigation system and to the environment, along the routes traversed. In conclusion, the empirical findings emphasize the importance of understanding human navigation behavior in relation to automatic (intelligent) navigation systems in real-world environments in order to ensure human skill development that will be necessary for everyday activities in a prospectively smart, autonomous city.

Walk and Learn: Effects of Human-Centered Navigation Systems on Pedestrians' Navigation Behavior

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Abstract

A city of the future is likely to be one where people, sensors, and the environment fuse together into one interconnected, dependent, and intelligent system - a smart city. Accordingly, navigation in a smart city will also change drastically, as intelligent navigation systems will autonomously guide people from one place to another. Using these automated systems, people will be able to navigate to their destination more efficiently, but these systems also appear to decrease cognitive development relevant to learning and memory in everyday activities. By relying more on a navigation system rather than relevant features in the environment, humans may lose the ability to acquire spatial knowledge that, amongst other things, ensures brain development. It is known that people develop these essential cognitive abilities for everyday situations when using analog maps. However, little is known about how analog and automated navigation assistance can be combined to ensure efficient navigation without losing the ability to acquire spatial knowledge. This thesis aims to understand the relationship between a human navigator and partly automated navigation systems in real-world environments, as most navigation experiments up until now have only assessed human behavior and spatial knowledge acquisition in virtual labs.

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systems and with the environment traversed. I designed partly automated navigation systems by systematically analyzing cognitive processes between human-centered (a low level of automation) and system-centered (a high level of automation) navigation system designs. Data on navigation performance, interactions with the navigation system, and mobile eye-tracking recordings build the basis for the spatial analysis of pedestrian behavior in the real world. The methodology provides unique insights into the behavior of pedestrians using navigation systems in urban environments.

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Chapter 1

INTRODUCTION

Humans who attempt to navigate through an unknown environment often use a map for assistance. The invention of increasingly automated and intelligent navigation systems is now changing how humans interact with maps and their environment. Today, the slowest and most individually behaved inhabitants of cities are pedestrians who shape the micro-rhythms of streets. Unfortunately, navigation space for pedestrians is usually an afterthought in urban planning and navigation system development (O'Mara, 2019). The focus of current cities is the optimization of vehicle flow, for example with automated cars, primarily due to economic reasons (O'Mara, 2019). The structure of a city, and the information about it transmitted through navigation systems influences human navigation behavior and impacts on the perception and memory of that urban environment (Appleyard, 1970; Gladwin, 1970; Lynch, 1960; O'Mara, 2019). To date, little is known about how intelligent navigation systems influence navigation behavior and cognitive processes of pedestrians in an increasingly dynamic city environment (Dai, Thomas, & Taylor, 2018; O'Mara, 2019). To be able to predict and influence pedestrian navigation behavior in smart cities, we first need to understand the effects of current navigation systems on navigation behavior of pedestrians in real-world urban environments.

1.1 Motivation and problem statement

Envision that you have just stepped off a bus on your way to your friend's new apartment, but you have no idea where your friend's apartment is. Luckily, you

have your friend's address on your mobile device, which is equipped with a navigation system. You confidently follow the route suggested. As you arrive at your friend's apartment, you realize that your friend is not there, and that your device's battery is empty. In addition, you realize that you have lost your keys somewhere along the way. Would you be able to recall your route to the bus stop in order to search for your lost keys?

This scenario emphasizes that navigation is an everyday activity for humans. A crucial process for humans during navigation is to know where they are. During this process, humans actively take part in the navigation task, make decisions, and also learn the layout of their surrounding environment (Lynch, 1960). While taking in their surrounding environment, humans activate and develop a specific part of the brain, the hippocampus, and build a mental representation - or cognitive map - of their surroundings (Lynch, 1960; O'Keefe & Nadel, 1978; Tolman, 1948). The development of the hippocampus is important for spatial tasks, such as finding a way that has already been walked, and non-spatial tasks for everyday activities such as telling a story in the correct sequence (O'Mara, 2019). The spatial task of navigation is challenging for humans, particularly in unknown environments. For example, finding a friend's new apartment, getting to a company for a job interview in an unknown part of the city, or walking to a hotel from the train station, requires mental effort and navigation skills (Montello & Sas, 2006). In order to find their way around more easily, humans use spatial representations in the form of maps as navigational assistance (Allen, 2000; Slocum, McMaster, Kessler, & Howard, 2009). When navigating with a map, humans also use spatial skills such as aligning information on the map to the features in the environment, and vice versa (Richardson, Montello, & Hegarty, 1999).

However, the invention of automatic and increasingly intelligent (navigation) assistance can also create problems for humans. On the one hand, intelligent systems can make decisions on our behalf, and, thus considerably reduce human cognitive and physical effort (Allen, 1999; Sheridan, 2002). On the other hand, automated assistance takes over tasks that used to be performed by humans (Sheridan, 2002) which also shaped human skill development (O'Mara, 2019). Researchers agree that automation should only work in collaboration with the human user, and only in tasks that require external assistance (Norman, 2015; Sheridan & Parasuraman, 2005; Weiser, 1999). In the case of navigation, it is

relevant to know when automation assists humans and when it actually hinders navigation tasks at a possible cost to the person.

Automated navigation systems outperform static, analog navigation assistance, such as paper maps, with respect to planning an efficient route, finding the navigator on a map, or supporting navigators in reaching a destination without detours (W.-C. Lee & Cheng, 2008). The beauty of navigation systems is that humans can divert their full attention to somewhere else than the navigation task at hand, but with the cost that they are no longer in control of the task (Taylor, Brunyé, & Taylor, 2008). As a result, humans reduce their attention on relevant navigational features, e.g., landmarks (Ishikawa, Fujiwara, Imai, & Okabe, 2008), and spend less time acquiring and processing spatial information compared to when they are using analog maps (Dickmann, 2012). Humans slide into a more passive mode when navigating with automated navigation systems compared with analog maps, which in turn can reduce their environmental awareness (Chrastil & Warren, 2012). Reports of navigational errors and accidents are increasing because humans are blindly following a route suggested by their navigation system. In doing so, they reveal one of the biggest disadvantages of using automated maps: not knowing where they are coming from, where they currently are, and where they are headed (Lin, Kuehl, Schöning, & Hecht, 2017). Navigation systems change humans' natural skills such as updating their position relative to their starting point, attending to relevant environmental features, and simultaneously learning the environment as they deactivate and degrade the hippocampus (Dahmani & Bohbot, 2020; McKinlay, 2016). Consequently, navigation systems prevent humans from navigating in the same way that they used to (Montello, 2009).

Prior research indicates that navigation systems of the future should actively involve the human user in the navigation process to ensure proper human skill development. Humans should make their own navigation decisions and need to proactively turn their attention back to the navigation task at hand and to the traversed environment (Chung, Pagnini, & Langer, 2016; Parush, Ahuvia, & Erev, 2007). Furthermore, humans should also be in control of the automated navigation assistance (Kiefer, Giannopoulos, Anagnostopoulos, Schöning, & Raubal, 2017; Richter, Tomko, & Çöltekin, 2015) in order to ensure spatial knowledge acquisition during real-world navigation.

To date, studies in the lab and virtual environments are considerably greater in number than those in real-world settings (Dai et al., 2018). Little research has been done in collecting pedestrian navigation data in real-world outdoor environments (Huang, Schmidt, & Gartner, 2012), although the act of walking directly influences the development of navigational skills (e.g., orientation and spatial knowledge acquisition) as it activates all the human senses (Appleyard, 1970; Gladwin, 1970; O'Mara, 2019). Instead, researchers usually test participants' navigation behavior in controlled lab environments during vehicle driving (e.g., Merat, Jamson, Lai, Daly, & Carsten, 2014) or when flying a plane (e.g., Burigat & Chittaro, 2016). Besides testing participants in lab environments, previous research on navigation has focused on either improving navigation efficiency or spatial knowledge acquisition but has not explored the relationship between navigation efficiency and spatial knowledge acquisition. To ensure human skill development, system automation should not only support humans in the efficiency and effectiveness of the navigation process but should also simultaneously activate environmental perception and support spatial knowledge acquisition. The navigation system should activate all relevant areas of the human hippocampus during navigation by letting the navigators make decisions and to move through and experience the real environment (O'Mara, 2019; Parasuraman, 2000; Parush et al., 2007).

In response to the above mentioned research gap, this thesis will contribute to the understanding of automated navigation assistance on navigation behavior and spatial knowledge acquisition of pedestrians in real-world outdoor environments.

1.2 Research question and research approach

Analog and automated navigation assistance lead to different levels of performance in navigation efficiency and spatial knowledge acquisition. Figure 1.1 visualizes the impact of the type of navigation assistance on navigation efficiency and spatial knowledge acquisition. On the one hand, automated navigation assistance focuses on navigation efficiency (Figure 1.1 A), decreasing human spatial knowledge acquisition as a consequence. On the other hand, analog navigation assistance leads to low navigation efficiency but increases spatial knowledge acquisition (Figure 1.1 B). In order to ensure brain

development, skill acquisition, and retention in an increasingly digitally-assisted society, the goal of future navigation systems should not only be navigation efficiency but should also support the retention and, hopefully, the improvement of spatial knowledge. The goal of this thesis is to understand the relationship between navigation efficiency and spatial knowledge acquisition when navigating using a partly automated navigation system. The aim of a future system design is a partly automated navigation assistance (Figure 1.1 C) that splits cognitive processes between the system (reducing the effort for the human user) and the navigator (reducing the assistance from the system). To achieve this, I wish to address the following main research question:

> How can the advantages of analog (human-centered) and automated (system-centered) navigation assistance be combined to ensure navigation efficiency without losing the ability to acquire spatial knowledge?

In order to define partly automated navigation assistance, I systematically vary the level of automation (Parasuraman, 2000; Sheridan, 2002) visualized in Figure 1.1 D. A high level of automation can be defined as stronger system assistance and less cognitive processing from the human navigator (automated navigation assistance), while a low level of automation can be defined as lower system assistance and more cognitive processing from the human navigator (analog navigation assistance).

Specifically, I conducted two experiments to assess the navigation behavior of pedestrians and spatial knowledge acquisition in a real-world outdoor environment. Participants use different navigation system designs that vary in their levels of automation of cognitive processes that are relevant to navigation, such as self-localization (Willis, Hölscher, Wilbertz, & Li, 2009). To evaluate the participants' navigation performance, I apply standard navigation measures such as time to task completion or interactions with the digital map (Dillemuth, 2005). To understand the visual attention processes more deeply, I employ the eye-movement data collection method (Duchowski, 2017; Holmqvist et al., 2011). This thesis also proposes and evaluates a new empirical framework aimed to assess participants' spatial knowledge acquisition during real-world navigation. The proposed framework suggests a use-inspired, practical approach for

real-world experiments and aims to investigate studies with the highest ecological validity. In summary, this thesis shares new insights into how to collect and combine different data streams, and how to analyze pedestrian behavior data. The work shows the potentials and limitations of real-world experiments in the field of spatial cognition research.

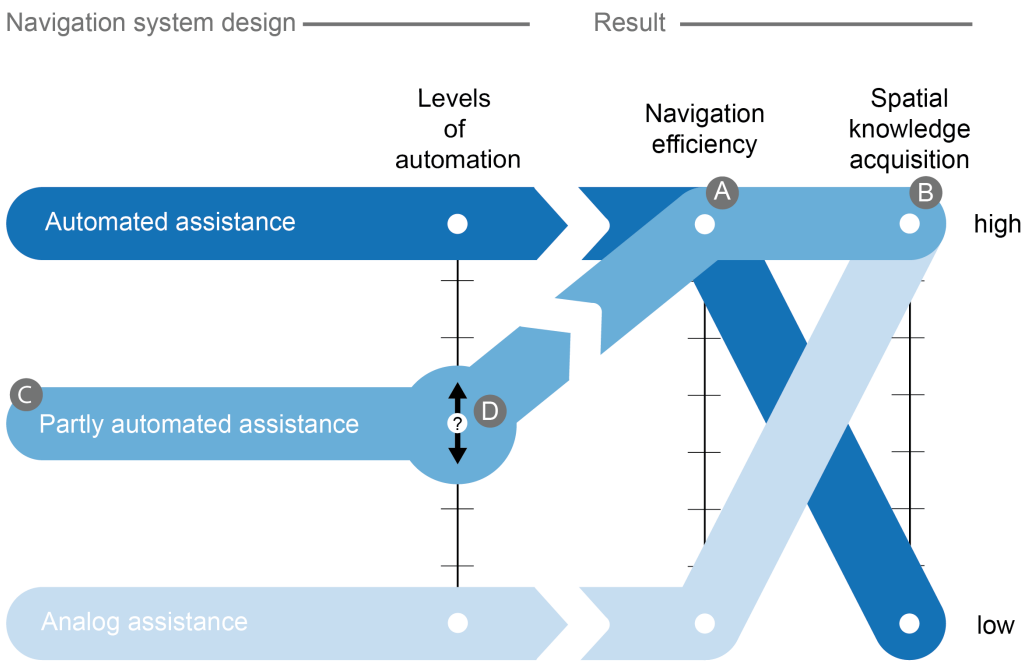

Figure 1.1: Research approach: To take the result of high navigation efficiency from automated assistance (A) and of high spatial knowledge acquisition from analog assistance (B) to design partly automated navigation systems (C). The approach aims to systematically vary the levels of automation of task relevant cognitive processes (D).

1.3 Contributions

In the future, human navigation will connect highly automated technology and skillful navigators within a complex intelligent system (McKinlay, 2016). Interdisciplinary cognitive research is necessary to understand how partly automated assisting systems can influence humans in the real world.

First of all, this thesis will contribute to a better understanding of human-system interaction in the context of navigation. The design of digital

assistants aims to adequately connect technological systems and their human users so that the user remains in overall control of the system, and that the system provides assistance but does not replace the person, thereby ensuring skill development (Sheridan, 2002). This thesis offers a unique understanding of the influencing factors of automation design and generates new insights into the distribution of a task's processes between humans and navigation systems during pedestrian navigation. The aim is to implement the advantages of analog (human-centered) and automated (system-centered) navigation assistance within a partly automated navigation system.

Second, this thesis contributes to the in-situ evaluation of pedestrian navigation. O'Mara (2019) states that "we know that the hippocampal formation in the brain, within which the cognitive map of the world is inscribed, receives input from all of our senses, plus feedback from the motor system." (p.82). Therefore, participants who can use all their senses and motor skills during an experiment can help researchers to better understand their behavior and to acknowledge the acquisition process during real-world navigation. I allow participants to perceive the environment with all their senses, but I will focus the analysis on vision, to find the gaze behavior patterns of pedestrians in the real world. In addition, this thesis introduces a novel empirical framework for evaluating human behavior and spatial knowledge acquisition in-situ. The framework offers use-inspired and practical scenarios that can be easily reproduced and developed further.

Third, this thesis will contribute to interdisciplinary research. The design of a city of the future should already consider humans and their natural skills in the stage of planning and decision-making (Lynch, 1960). This still holds true for smart cities because they can be steered with combined efforts from geospatial science, information and communication technologies, and social/cognitive sciences (Huang, Gartner, Krisp, Raubal, & Van de Weghe, 2018). Therefore, this thesis offers new insights into empirical data collection methods that link and connect collected human sensory data in order to better understand the relationship between humans, technology, and space. This thesis shows how navigation assistance can be systematically designed and tested with theories of human-system interactions with empirical methods developed for practice.

Finally, this thesis contributes to human society. To ensure an

attention-seeking, attractive, safe, and healthy environment for its citizens that can assist in the development of essential human brain function, it is important to consider two fundamental components for the design of the city of the future: the micro-rhythms of pedestrians and the structure of the environment (O'Mara, 2019). Promoting activation of specific parts in the brain during navigation not only develops spatial skills but also helps humans in executing many everyday activities that do not require spatial awareness. Therefore, this thesis aims to make an empirically validated contribution to how humans and systems could successfully interact in a prospectively autonomous, smart city.

1.4 Structure of the thesis

The thesis has seven chapters. Chapter 2 gives a literature review on definitions and characteristics of human navigation and system automation. A subsection on human navigation with automated navigation systems reports on empirical findings during navigation system use and highlights the research gap of missing empirical studies with pedestrians in real-world, outdoor environments. Chapter 3 presents the empirical WALK-AND-LEARN framework for testing human behavior and spatial knowledge acquisition in real-world outdoor environments, the stimuli of levels of automation in the design of navigation systems, and the measures of navigation behavior. Chapters 4 and 5 subsequently outline the two experiments on how partly automated navigation systems influence human navigation behavior and spatial knowledge acquisition. In Chapter 6, I discuss how the two empirical studies contribute to answering the main research question on how the advantages of analog (human-centered) and automated (system-centered) navigation assistance can be combined to ensure navigation efficiency without losing the skill to acquire spatial knowledge. Additionally, I critically examine the potential and limitations of the empirical work. Finally, Chapter 7 summarizes the main findings and the contributions of the thesis to research on human-system interactions regarding pedestrian navigation in the real world. Additionally, an overview on the design of future navigation systems and empirical studies shows how smart cities can ultimately become more human-centered and less system-centered.

Chapter 2

RELATED WORK

Studying pedestrian navigation in the digital age builds on existing knowledge of navigation in general, cognitive processes during navigation, and human interactions with traditional and automated (navigation) systems. All of these processes are influenced by various factors, such as the environment, which all have positive and negative effects for the navigator. From these empirical findings, I have identified design guidelines for navigation systems, before reviewing the few studies that analyze eye-tracking data in real-world, outdoor environments. To get to this point, I start by explaining what navigation is and how this term is used in the thesis.

2.1 Navigation

Navigation is an essential human skill that involves the process of encoding environmental cues in order to convert them into information in order to orient ourselves and navigate within the environment (Nazareth, Huang, Voyer, & Newcombe, 2019). Navigation consists of two major components: locomotion and wayfinding (Montello, 2005), both of which are influenced by the environment (Carpman & Grant, 2002; O'Mara, 2019; Weisman, 1981).

Locomotion refers to the actual bodily motion of human movement through their nearby surroundings (O'Mara, 2019) and involves the interplay of the sensory and motor systems to avoid obstacles, to cross roads, or recognize different road characteristics (Montello, 2005). Locomotion is different for pedestrians and vehicles because the time and perspective to perceive and attend

to objects in the environment vary due to velocity differences and the spatial restrictions of either a pavement or a road (Gaisbauer & Frank, 2008). A human's natural self-locomotion is walking. This usually happens automatically because the body and the brain have developed this ability to become one of the first tasks a person learns (O'Mara, 2019). When humans walk, they "read" the world with all their senses which activate their brains in various forms (O'Mara, 2019). Most importantly, walking influences hippocampal formation - the part of the brain that is responsible for learning, planning, and memory tasks (O'Mara, 2019). It is precisely these cognitive tasks represent the second component of navigation: wayfinding.

Wayfinding is the planning process of finding a destination. Planning involves several separate processes such as using landmarks for orientation, making decisions at intersections, and planning a route to a destination (Montello, 2005; Wiener, Büchner, & Hölscher, 2009). Successfully finding a destination is an essential human behavioral trait (Montello, 2005) requiring knowledge about one's own location and the sequence of environmental cues, turns, segments, and sights along the route (Downs & Stea, 1973; O'Keefe & Nadel, 1978). During wayfinding, humans have to perform several important cognitive processes, one of which is self-localization. Self-localization is defined as the specification of one's own location in an environment (Meilinger, Hölscher, Büchner, & Brösamle, 2007). During this process, environmental characteristics (e.g., salient landmarks) support the formation of mental spatial representations, particularly when located at intersections (Denis, Michon, & Tom, 2007; Raubal & Winter, 2002). Allocation of attention is another cognitive process that is essential for navigation. Allocation of attention can be defined as directing one's attention to a specific object in the environment, such as a landmark or an intersection (Chrastil & Warren, 2012; Richter & Winter, 2014). What humans see and what tasks they perform defines a navigator's attention (Ware, 2013). While researchers do not agree on whether attending to an object for a longer period of time (Rayner, 2009) or attending to the object multiple times (Couclelis, Golledge, Gale, & Tobler, 1987; Tatler, Gilchrist, & Land, 2005) leads to a higher cognitive processing of that object, they do agree that this object acts as an anchor point for memory, and supports spatial knowledge acquisition.

2.1.1 The acquisition of spatial knowledge during navigation

Acquiring spatial information is crucial to orient and navigate within a particular space without losing the way (Montello, 2005; Siegel & White, 1975), and occurs when making decisions and interacting with the environment (Block, 1998; Lobben, 2004). Tolman (1948) was the first to mention that wayfinding leads to the formation of a kind of a map in the head - a cognitive map - where spatial locations are cognitively processed and stored. Lynch (1960) described five characteristics of a city that activate perceptions of an environment: landmarks, paths, nodes, edges, and districts. Based on these characteristics, Siegel and White (1975) highlighted that mental representations of space are not perfect, but are fragmented, distorted, and hierarchically constructed. The authors defined three kinds of spatial knowledge relevant to form a cognitive map: landmark, route, and survey knowledge. Landmark knowledge is the ability to remember and recall acquired objects from the environment (Siegel & White, 1975). If the sequence of these landmarks can be interlinked, humans will be able to acquire route knowledge, which can also be defined as procedural knowledge (Freundschuh, 2009; Thorndyke & Hayes-Roth, 1982). If landmarks and routes can be structured in a layout-based representation involving direction and distance estimations, then this is known as survey or configurational knowledge (Hirtle & Hudson, 1991; Siegel & White, 1975).

However, critical arguments have emerged on whether the three types of spatial knowledge can really be (strictly) separated, and how the first-person perspective influences spatial knowledge acquisition (Freundschuh, 2009; Montello, 1998). Tversky (1993) stated that spatial knowledge is actually a cognitive collage in which the fragments of remembered spatial features overlap each other. Previous research has also established that gender (Hegarty, Montello, Richardson, Ishikawa, & Lovelace, 2006; Hund & Gill, 2014; Nazareth et al., 2019) as well as individual differences, such as spatial rotation ability (Hegarty et al., 2006) or sense of direction (Burte & Montello, 2017), can influence spatial knowledge acquisition. However, these will not be discussed further as this thesis does not focus on individual differences or spatial abilities, although we do need to determine how the structure and features of the

environment can influence navigation behavior and spatial knowledge acquisition.

2.1.2 The influence of the environment on navigation

Navigators have external information available to them during navigation: the environment. An environment can be real or virtual, indoors or outdoors, complex or simple, familiar or unfamiliar, etc. Such environments share characteristics such as landmarks, routes, or regions (Lynch, 1960). Landmarks are defined as "geographic objects that structure human mental representations of space" (Richter & Winter, 2014, p.7), and form the basic element of spatial knowledge (Chrastil & Warren, 2012; Siegel & White, 1975). According to Sorrows and Hirtle (1999), landmarks can be divided into three categories: visual (visually distinctive), structural (those that stand at important locations, usually at intersections and decision points), and semantic (the meaning stands out). These categories also depend on the journey direction and the structure of the route. A route can be characterized by a starting point, a destination location, and intersections (Lovelace, Hegarty, & Montello, 1999; Lynch, 1960). Intersections (choice or decision points) along a route do not all have the same importance, but navigation errors are possible at all of them (Allen, 2000). Intersections divide a route into segments, each segment being a small region with its own characteristics. A route usually features several intersections, of which some are turning points. Complex turning points are usually difficult to navigate as several decisions have to be made, such as which street to take or which streets to cross (Liao, Dong, Peng, & Liu, 2017).

Locomotion through and the structure of an environment influence spatial knowledge acquisition during navigation (Appleyard, 1970; Carpman & Grant, 2002; Dai et al., 2018; F. Martin & Ertzberger, 2013; O'Mara, 2019). The appearance and structure of the environment is important for humans to be able to process spatial information and to successfully make their way from a starting point to a destination (Carpman & Grant, 2002). However, the formation of a mental representation of an environment is demanding and is limited by humans' attentional capacity (Downs & Stea, 1973; Münzer, Zimmer, Schwalm, Baus, & Aslan, 2006; Siegel & White, 1975; Wahn & König, 2017; Weisberg & Newcombe, 2018). Therefore, humans have developed ways to minimize physical and

cognitive effort (O'Mara, 2019) by externalizing the cognitive processes to a navigational assistant (Wiener et al., 2009).

2.1.3 Wayfinding assistance to support navigation

Nowadays, people often use navigational assistance to support demanding cognitive processes such as wayfinding tasks (Allen, 1999). To get from one place to another in an efficient and effective manner, humans use different representations (e.g., route instructions, signs, etc.) for guidance (Allen, 1999; Slocum et al., 2009). One form of navigation assistance is a map which helps in finding the way from one place to another in both known and unknown environments (Ludwig, Müller, & Ohm, 2014; Montello & Sas, 2006; Nazareth et al., 2019; Wiener et al., 2009). Maps have been in existence for more than 4,500 years and have been constantly changing because of environmental transformations, observational tools, techniques, etc. (Slocum et al., 2009). A traditional cartographer had to make decisions on what to put on a map, what scale to use, which level of generalization to apply, which map projection to display, and what symbolization to use for particular information depending on what the map would be used for (Slocum et al., 2009). A user of such a traditional or analog map (i.e. paper map) needs first to localize themselves, then to plan and decide on a route by themselves, and finally to orient themselves within the space (Thorndyke & Hayes-Roth, 1982). These processes require attention to the environment and to acquisition of information about environmental properties such as spatial configurations and landmarks (Thorndyke & Hayes-Roth, 1982). In other words, assistance in the form of a map changes cognitive processes during wayfinding and challenges two important cognitive processes during navigation: self-localization and allocation of attention (Lobben, 2004; Wiener et al., 2009). To localize oneself with the aid of navigational assistance, humans have to match the information from the map (usually from a bird's-eye perspective or allocentric/top-down perspective) to the environment (first-person perspective or egocentric) view (Aretz & Wickens, 1992; Lobben, 2004; Meilinger, Franz, & Bülthoff, 2012; Wang, 2017). Humans who use a map have both an object and the environment to allocate their attention to. They have to process information from both sources to successfully

navigate from one place to another (Gardony, Brunyé, Mahoney, & Taylor, 2013; Ishikawa et al., 2008; U. Lee et al., 2014; Willis et al., 2009). With developments in digital technology, navigational assistance has become automated, which has consequences for human navigational behavior. But first, what exactly is automation?

2.2 Automation

The word automation comes from the word "automatic", which is defined as "[of a device or process] working by itself with little or no direct human control." and "done or occurring spontaneously, without conscious thought or attention." [1]. Automation is therefore the result of doing something that usually a human would do (Parasuraman, Sheridan, & Wickens, 2000). "The classic aim of automation is to replace human manual control, planning and problem solving" (Bainbridge, 1983, p.775). These three replaced processes are important tasks for humans in terms of various life aspects such as system design, coordination, society, etc. (T. Martin, Kivinen, Rijnsdorp, Rodd, & Rouse, 1991). The goal of automation should be to support humans (e.g., in avoiding errors), augment their skills and abilities (e.g., with pattern recognition), and to reduce human control processes (Janlert & Stolterman, 2017b; T. Martin et al., 1991). Therefore, automated replacements can have positive effects for physically, cognitively, and temporally demanding tasks, or for people who have physical or mental impairments (Froehlich et al., 2019). Accordingly, automatic systems should both complement (Sheridan, 2002) and actively involve humans in the process whenever necessary (Parasuraman, 2000). Therefore, the main advantage of automatic systems is that they can perform tasks that used to be done by humans in a more efficient or effective way. Problems arise when automation does not work properly, or when humans are not involved and not seen as a collaborator of the system (Norman, 2015). However, Bainbridge (1983) and T. Martin et al. (1991) suggested that the more automated a system gets, the more important the input from the human user. In light of this, researchers have begun to evaluate which tasks or processes should be automated by the systems

[1] https://www.lexico.com/en/definition/automatic (access by 02/07/2020)

and which should be executed by the human user, and what effects automation has on human behavior (T. Martin et al., 1991; Parasuraman et al., 2000). Careful consideration in implementing automatic tasks are the basis for justifying its implementation (T. Martin et al., 1991). However, automation means that tasks and processes change and have intended and unintended effects for human users (Bainbridge, 1983; Janlert & Stolterman, 2017b), meaning that frameworks for structuring automation have also been proposed.

2.2.1 Levels of automation

Automation is not binary - either a task is automatically executed by the system or it is manually performed by the human. However, it can have several gradations (Parasuraman et al., 2000). Different levels (or degrees) of human interaction with automation are possible, namely when the system and the human share tasks (Parasuraman et al., 2000). These types range from high levels of automation where decisions and actions are automatically executed by the system without human interaction, to low levels of automation where the human makes decisions and actions without any assistance from the system. One such example by Parasuraman et al. (2000) is depicted in Table 2.1.

10.	The computer decides everything, acts autonomously, ignoring the human
9.	informs the human only if it, the computer, decides to
8.	informs the human only if asked, or
7.	executes automatically, then necessarily informs the human, and
6.	allows the human a restricted time to veto before automatic execution, or
5.	executes that suggestion if the human approves, or
4.	suggests one alternative
3.	narrows the selection down to a few, or
2.	The computer offers a complete set of decision / action alternatives, or
1.	The computer offers no assistance: human must take all decisions/actions.

Table 2.1: To complete a task, each process can be automated on a range from 1 (low) to 10 (high). Low levels of automation indicate higher human engagement, while high levels of automation specify lower human engagement in the process during system use. Table replicated from Parasuraman et al. (2000)

These levels could vary from low (no system assistance; the human makes all decisions and performs the actions) to high (system makes all the decisions; no human intervention possible). Sheridan (2002) clarified that the lowest number indicates the least automation, while the highest number defines the highest automation in a system design. Parasuraman et al. (2000) highlighted that each process of a task could be automated on a level from 1 to 10 resulting in several levels of automation implemented in one system in order to achieve the task's goal. For example, one process could be implemented on Level 1 and another process on Level 8 resulting in a partly automated system whereby the human still retains some control. These levels indicate that a process can be partially or fully executed by a system (that used to be done by humans) usually in a more time-efficient and effortless way (Parasuraman & Riley, 1997). To choose an appropriate level of automation, each process during task execution should be individually evaluated (T. Martin et al., 1991). If a task is at low risk and/or is under time-critical circumstances, Parasuraman (2000) suggested the implementation of a higher level of automation as this will lead to more efficient task execution.

System designs with lower levels of automation usually consist of an interface to allow for human interaction. For example, conventional interfaces demand manual action from a human, such as pressing a button, typing information on a keyboard, or interaction with a touchscreen (Janlert & Stolterman, 2017b; Parasuraman et al., 2000; Wolter & Kirsch, 2017). If a button only has one function, the decision (when) to press the button is still left to the human while the process behind the button is executed by the system. This type of automation is called action automation (Parasuraman et al., 2000), whereby the human explicitly interacts with the system (Janlert & Stolterman, 2017b; Wolter & Kirsch, 2017). However, more intelligent, modern systems are more proactive in providing information (Wolter & Kirsch, 2017). Intelligent systems usually have an adaptive character that began to be implemented within systems during the 1970s (Scerbo, 1996). An example of the adaptation design is a context-dependent message or graphic that pops up on an interface. This type of automation is called adaptive automation (Parasuraman et al., 2000), whereby the human implicitly interacts with the system and decision-making behavior is not required (Janlert & Stolterman, 2017b). Janlert and Stolterman (2017b) and

Wolter and Kirsch (2017) mentioned the proactive behavior of the system because the system acts automatically and imitates tasks that humans would be doing in this situation. In both types of automation (action and adaptive), interactions between a system and a human are always present. A fully automated system is still dependent on human input at one stage (even when it is in the stage of design or measuring human response), which still makes humans the main driver of the automation (T. Martin et al., 1991). Therefore, interactions can either demand a considerable amount of attention or they happen unconsciously, although humans are creating or influencing the behavior of the system. Either way, these systems influence human behavior (Janlert & Stolterman, 2017b).

2.2.2 Effects on human behavior

Automated systems influence human behavior in positive and negative ways. One of the most important positive effects of automated systems is that they reduce the physical and cognitive effort of the human users (Parasuraman & Riley, 1997). For example, if a time-consuming or tedious task is automated, humans could have more time to focus on other tasks (Brey, 2006; Sheridan, 2002). Having more time makes humans feel less stressed as they are able to delegate work (O'Mara, 2019) and to be in control of a situation. In this way, they can complete several tasks within a shorter amount of time (Brey, 2006). If humans interact with the system (e.g., by clicking on a button), then it will automatically execute a task. Therefore, a system with specific interactions can support humans in attending to information, which would otherwise demand more effort to gather (Ware, 2013). Furthermore, a system with the right level of active effort, control, and power can enhance a human user's feelings of trust in the system, as well as increased levels of achievement and satisfaction when a task is completed (Bainbridge, 1983). Again, these feelings have an impact on cognitive processes and knowledge acquisition (Kool, McGuire, Rosen, & Botvinick, 2010; O'Mara, 2019). A system with personalized information can even guide users to attend to and learn from the environment (Brey, 2006; Kool et al., 2010).

Attention to goal-relevant information is an important human skill that is used to evaluate and acquire information for everyday decision-making activities

(Guinote, 2017). To acquire new knowledge and to connect it with existing knowledge is essential for ensuring recognition (Ware, 2013). The recognition of objects and a human's active state are positively related, highlighting that both the physical and cognitive activity of humans is important for perceiving their environment (Gibson, 1962). However, humans tend to use the least (physical and cognitive) effort when using automated systems (Kool et al., 2010), but also struggle to resist interactive elements (e.g., buttons) by simply using these elements without any intention. These unintended actions lead to humans becoming distracted from the task at hand (Janlert & Stolterman, 2017b). When getting distracted by the system, humans change the process of information collection and decrease situational awareness (Guinote, 2017; Parasuraman et al., 2000; Zacks & Tversky, 2001). While using highly automated systems, motor skills (e.g., hand interactions) and perceptual skills can decrease (Johansson, 1989; O'Mara, 2019; Parasuraman et al., 2000). Additionally, if a system acts against the human's expectation, the consequence to the human is a loss of control, power, and individual autonomy (Berlin, 1969; Brey, 2006; Guinote, 2017). This then leads to psychological pressures, because the human user of the system has to decide whether to trust the system (that should act upon its own needs) or one's own assessment in that situation (Brey, 2006). Automated systems lead to negative effects on human behavior such as distraction, degradation of skills, control loss, and even a loss of freedom (Brey, 2006; Guinote, 2017; Johansson, 1989). Therefore, it is essential for researchers to provide guidelines for system designs based on these findings.

2.2.3 Guidelines for system design

Based on the positive and negative effects of automation on human behavior, the following list presents guidelines of what systems should implement:

- Human-centered automation (Sheridan & Parasuraman, 2005);
- Context-aware design, in which the context is both the user (cognitively) and the environment (physically) (Johansson, 1989; O'Mara, 2019; Parasuraman & Riley, 1997; Wolter & Kirsch, 2017);
- The correct number of challenges and interactions in order to develop skills,

such as learning and acquiring information (Janlert & Stolterman, 2017b), to make decisions (Guinote, 2017), to govern oneself (Brey, 2006; O'Mara, 2019), and to perceive our environment (Zacks & Tversky, 2001);

- Control of the human user to ensure a feeling of power and trust (Brey, 2006; Guinote, 2017);
- Individual (Brey, 2006; Kool et al., 2010) and cultural differences (T. Martin et al., 1991); and
- Collaborative tasks and processes with a human user (Johansson, 1989; Parasuraman, 2000; Sheridan, 2002).

When considering these suggestions, system engineers should acknowledge that the goal of automated systems is to ensure an interplay between the system and the human (Sheridan, 2002) without the system degrading human abilities and trust (Brey, 2006). Since automated systems affect human behavior in many different aspects, navigation with automated systems should also be examined.

2.3 Navigation with automated systems

Navigation systems primarily aim to deliver easy-to-understand navigation instructions that support people in reaching a destination more quickly and help reduce cognitive load during wayfinding (Allen, 1999; Chen & Stanney, 1999). As I discussed in Sections 2.3.2 and 2.3.3, humans change their behavior using these systems compared to not using them or by using traditional navigation assistance (Montello, 2009). But first, I will attempt to answer whether automation has changed navigational assistance.

2.3.1 Navigation assistance is automated

A key aspect of navigation systems is the integration of the global positioning system (GPS) to determine a person's current location. The navigation system constantly updates the location of the person and displays their location on the digital map (Kaulich, Heine, & Kirsch, 2017; Rinner, Raubal, & Spigel, 2005; Schwinger, Grün, Pröll, Retschitzegger, & Schauerhuber, 2002). With such

location-aware systems, the possibility of, for example, automatically displaying information depending on the users' current location, is another achievement in automating navigation (Cheverst, Mitchell, & Davies, 2001). In research, context-dependent displays have been developed to automatically detect and integrate landmarks into maps (Duckham, Winter, & Robinson, 2010; Raubal & Winter, 2002; Roger, Bonnardel, & Le Bigot, 2011; Sorrows & Hirtle, 1999; Steck & Mallot, 2000). Three other key aspects of navigation systems are the opportunity to change the scale of the map by zoom interfaces (Baudisch & Rosenholtz, 2003; Dickmann, 2012; Ishikawa & Takahashi, 2013; Kray, Elting, Laakso, & Coors, 2003; Ware, 2013; Willis et al., 2009), the ability to efficiently calculate and visualize (e.g., the shortest) route to a destination (Ishikawa et al., 2008), and automatically orienting the map in the direction headed (McKenzie & Klippel, 2016). The tasks that a person would normally do themselves (localizing oneself, planning a route, allocating attention to relevant landmarks, making decisions along the way) can now be efficiently performed by the automatic design solutions in navigation systems. However, what happens if the system runs out of battery or the satellite reception goes down? Humans get lost, mainly because they rely on the GPS signal and related technologies (Montello, 2009). It is still not known to what extent the adaptation process of location-based information should be automated, and to what extent social and behavioral implications can be expected (Huang et al., 2018). To address this research problem, empirical studies have examined the effects of navigation systems on the human attention behavior.

2.3.2 Effects on human attention behavior

Münzer et al. (2006) found that pedestrians using navigation systems show better navigation performance (i.e., taking less time to reach their destination) compared to using analog maps. Also, Dickmann (2012) and W.-C. Lee and Cheng (2008) showed that people using navigation systems are more time-efficient and effective in finding the route than people using analog (i.e. paper) maps. The reasons for this are that the tasks of planning a trip, searching for relevant information, and choosing routes are no longer necessary with navigation systems and reduce the attention on relevant information for the task.

Furthermore, automated maps lead to lower cognitive workload during the whole trip. The blue dot that displays the navigator's current location, or the automatic centering of the map in the walking direction, are two examples of lower workload while increasing navigation efficiency while using the navigation system. These positive effects on navigation performance with automated maps show that the locomotion component of navigation is emphasized over the wayfinding - planning and decision-making - component, when using navigation systems (Montello, 2005). However, decision-making is an essential human behavior that supports interactions with the surroundings (Golledge & Stimson, 1997). If decision-making is taken away from humans by automated systems, then they will not attend to the information from their environment that would otherwise have led to a decision thy could have made. Attention is defined as the collection and processing of information (Holmqvist et al., 2011). A navigation system automatically selects and depicts environmental properties (e.g., landmarks) without any user intervention, which leads to decreased attentiveness to relevant environmental properties (Taylor et al., 2008). The use of a navigation system reduces what properties from the surroundings a navigator selects and diminishes the navigator's allocation of attentional resources (Ishikawa et al., 2008). Consequently, the navigator does not attend to their traversed surroundings but instead reallocates attention toward the automated navigation system (Gardony et al., 2013; Willis et al., 2009). Koletsis et al. (2017) reported that people have often missed important environmental navigational cues because they were watching the navigation system.

During navigation system use, different environments rival for human attention: the physical environment and the assistance in the form of the navigation system (Janlert & Stolterman, 2017b). The distribution of human attentional resources leads to a segmentation of attention (Parasuraman, 2000; Willis et al., 2009). The navigator has to constantly switch between a survey perspective offered by the navigation system and a route perspective such as the first-person view (Dai et al., 2018; Gardony et al., 2013). Several studies have demonstrated that automated guidance divides a navigator's attention between the navigation system and the environment (Gardony et al., 2013; Ishikawa et al., 2008). For example, a constantly updating GPS signal (e.g., a blinking light) on a navigation system can induce such attentional division. As the navigator's

position is continuously being updated, the visual tracking of the GPS signal distracts the navigator's attention from the surroundings and toward the system (Ishikawa et al., 2008). Navigation systems seem to change how humans attend to the environment (Parush et al., 2007). When continuously relying on these kinds of positional updates, we do not attend to the information that the traversed environment provides, meaning that we lose the ability to select relevant navigational information (Parush et al., 2007). Willis et al. (2009) identified that the fragmentation of attention and the lack of matching the information of the navigation assistance and the environment are major concerns for cognitive processes. To return their attention to the surroundings, users have to proactively make decisions (Chung et al., 2016; Kiefer, Giannopoulos, Anagnostopoulos, et al., 2017; Parush et al., 2007).

A few scholars have begun to explore possible interventions during assisted wayfinding. A navigation system should invite a navigator to proactively attend to their environment (Kraft & Hurtienne, 2017) and thereby increase their cognitive resource allocation for a task (Parasuraman et al., 2000). System interventions should be controllable by the navigator and should be adaptable and context-dependent (Kiefer, Giannopoulos, Anagnostopoulos, et al., 2017; Parasuraman, 2000; Richter et al., 2015; Sheridan, 2002). However, interventions such as context-dependent notifications can also distract a user from other activities and can increase their attention allocation on the system and away from the surroundings (U. Lee et al., 2014; Pielot & Rello, 2017). People seem to worry that they may miss important information if they are not attending to these notifications (Pielot & Rello, 2017). Navigators using navigation systems tend towards a state of passive behavior, which in turn negatively affects important cognitive processes such as spatial knowledge acquisition (Mondschein & Moga, 2018).

2.3.3 Effects on spatial knowledge acquisition

Navigation systems consume most of a pedestrian's attention, leading to passive decision-making behavior (Mondschein & Moga, 2018), decreased spatial awareness, reduced spatial knowledge acquisition (Chen & Stanney, 1999; Gardony et al., 2013; Parush et al., 2007), and even to fatal accidents

(Lin et al., 2017). However, if the navigation system fails, navigators will have to rely on their acquired knowledge. This is difficult because if properties along a route are not mentally processed, spatial knowledge will decrease (Hirtle & Raubal, 2013; Huang et al., 2012; Münzer et al., 2006; Parasuraman, 2000; Parush et al., 2007).

Chrastil and Warren (2012) state that "(...) full route knowledge and survey knowledge appears to require the intention to learn, implying the need for attention to the relevant spatial relation. (...) intentional encoding appears to be necessary for place-action association, reproducing a route, and spatial relations between landmarks" (p.14). Participants who knew that they had to learn a route (intentional learning) showed a better route knowledge than participants who did not realize that they would be asked to memorize a route (incidental learning) (Chrastil & Warren, 2012). The ability to recall objects for the two different learning types is different. Intentional learners are better at recalling the location of objects, while incidental learners are better at recalling the names of objects (Chrastil & Warren, 2012; Van Asselen, Fritschy, & Postma, 2006). Therefore, if a navigation system directs attention to specific properties in the surroundings, humans would actively encode spatial information (Chrastil & Warren, 2012). One way to do this is to engage navigators in a spatial location quiz, thus associating locations with a particular question, or to make them perform an otherwise automated action manually in order to improve their mental spatial representations (Chrastil & Warren, 2012; Parasuraman et al., 2000; Parush et al., 2007).

The passive state of humans when using navigation systems is found to be one of the major cognitive problems regarding spatial knowledge acquisition (Willis et al., 2009). An increasing number of empirical studies have investigated how active and passive roles during navigation may influence the attention paid to the immediate surroundings of a navigator and may support or hinder the formation of mental spatial representations, as a consequence. Münzer et al. (2006) contended that added active effort during assisted navigation leads to spatial learning benefits and introduces the active learning hypothesis. The hypothesis states that incidental learning happens when spatial information is encoded, converted, and acquired. Therefore, when actively making decisions and facing consequences, humans are once again able to connect with their

surroundings (Bakdash, Linkenauger, & Proffitt, 2008). Gardony et al. (2013) explored the relationship between navigators' attention to the surroundings and their spatial decision-making while using a navigation system. They discovered that if both decision-making with and attention to the traversed environment decreased, the navigators' spatial knowledge acquisition would also decrease. Attentiveness toward the environment (Klippel, Hirtle, & Davies, 2010), the level of control, and the amount of decision-making (Bakdash et al., 2008) are suggested to yield differences in spatial knowledge acquisition.

Therefore, to increase spatial knowledge acquisition, navigators need to interact with both the navigation system and their surroundings (Willis et al., 2009). Researchers also addressed how different environments change spatial knowledge acquisition (Ishikawa et al., 2008; Münzer et al., 2006; Parush et al., 2007; Willis et al., 2009). They found that the structure of urban environments can stimulate active participation in navigation and can influence human behavior (Barsalou, 1988; Carpman & Grant, 2002; Emo, 2014; Mondschein & Moga, 2018; Yates, 2017). However, architecture and urban design is not the focus of this thesis, so the research findings on these topics will not be detailed here.

2.3.4 Guidelines for navigation system design

Researchers who compared different kinds of navigation assistance found that modern navigation systems have a negative impact on the formation of mental spatial representations (Bakdash et al., 2008; Hirtle & Raubal, 2013; Ishikawa et al., 2008; Ishikawa & Takahashi, 2013; Klippel et al., 2010; Parush et al., 2007; Richter, Dara-Abrams, & Raubal, 2010; Willis et al., 2009). For example, Münzer et al. (2006) found that pedestrians using analog maps perform better in spatial knowledge and orientation tasks compared to when they were using navigation systems. In particular, GPS signals implemented in navigation systems that facilitate humans' cognitive process "self-localization" were found to negatively influence spatial knowledge acquisition (Ishikawa et al., 2008; Krüger, Aslan, & Zimmer, 2004; Minaei, 2014). As a consequence of the detrimental spatial knowledge acquisition with navigation systems (Bertel, Dressel, Kohlberg, & von Jan, 2017; Parush et al., 2007; Willis et al., 2009), digital maps should

allow a navigator to proactively allocate their attention to the environment (Kraft & Hurtienne, 2017) and simultaneously increase cognitive resource allocation for the task (Parasuraman et al., 2000) and increase their spatial knowledge acquisition (Parush et al., 2007). Willis et al. (2009) summarized the proposed design solutions for navigation systems below.

- The user should occasionally control the receipt and approval of information.
- The user should receive the information in short segments. Within these segments, a user can examine the information again to increase spatial knowledge acquisition. Navigation systems should have the ability to switch themselves off when nothing important happens to reduce attention on the system.
- Users should use existing knowledge, similar locations, and common cues to match objects in the map with objects in the real-world environment.

2.4 Eye-tracking for research in spatial cognition

Eye-tracking is a technology that records a navigator's gaze behavior during navigation from a first-person perspective (Duchowski, 2017; Goldberg & Kotval, 1999; Holmqvist et al., 2011; Kiefer, Giannopoulos, Raubal, & Duchowski, 2017). The method of collecting data with an eye-tracker has become a popular tool with which to analyze navigation behavior (Blascheck et al., 2014; Kiefer, Giannopoulos, Raubal, & Duchowski, 2017). An eye-tracker records gaze duration and behavior which can be interpreted as a measure of cognitive function and the visual complexity of the scene (Duchowski, 2017; Goldberg & Kotval, 1999). Mobile eye-tracking is particularly interesting in navigation scenarios because it can measure a human sense (gaze behavior) in real-world environments relatively accurately and can thus provide an indication of the information acquisition process (Kiefer, Giannopoulos, Raubal, & Duchowski, 2017).

To date, navigation studies using eye-tracking have focused on behavioral effects in different ways. Haupt, Van Nes, and Risser (2015) compared gaze behavior during vehicle driving with paper and digital route instructions.

Ohm, Bienk, Kattenbeck, Ludwig, and Müller (2016) evaluated self-localization ability with different map perspectives based on salient objects. In desktop environments, Liao et al. (2017) compared visual attention between 2D maps and 3D geo-browsers, Merat et al. (2014) analyzed how drivers regained control from automated vehicles, and Lander, Herbig, Löchtefeld, Wiehr, and Krüger (2017) introduced an approach of inferring landmarks for navigation instructions from mobile eye-tracking data. Regarding environmental characteristics, Emo (2014) suggested that space-geometric measures influence the gaze at intersections, Simpson, Freeth, Simpson, and Thwaites (2018) highlighted the importance of street edges, Schwarzkopf, Büchner, Hölscher, and Konieczny (2017) compared perspective-taking by comparing gaze directions between individual and collaborative wayfinding, Wenczel, Hepperle, and von Stülpnagel (2017) compared gaze behavior between navigators who incidental and intentional learned the environment, and Liao, Dong, Huang, Gartner, and Liu (2019) inferred navigation tasks based on eye movement characteristics. Most recently, Bécu et al. (2019) analyzed body and gaze behavior and discovered that older adults focus on geometric elements while younger adults prefer to use landmarks during navigation.

To the best of my knowledge, only three studies thus far have analyzed gaze behavior in-situ during assisted navigation in real-world environments. Haupt et al. (2015) compared the gazing behavior of drivers between analog route instructions and navigation systems with GPS. The study, which focused on assisted car drivers' fixations in movement direction (i.e., forward, right, left, rear-mirror, and over the shoulder) showed a significant difference in fixations to the side when using either a navigation system or printed route instructions (Haupt et al., 2015). These authors argue that the analog assistance forced the drivers to find relevant orientation information in the environment, meaning that their proportion of fixations to the side was higher and longer than when using a navigation system. When using the printed route instructions, the drivers were looking for points used to orient themselves, while drivers with navigation systems were more likely to be looking out for hazards. Kiefer, Giannopoulos, and Raubal (2014) investigated the cognitive process of self-localization. Using mobile eye-tracking technology in an outdoor environment, they showed that participants successfully located themselves when they were looking at relevant

(compared to irrelevant) landmarks in order to find themselves on the map. Ohm, Müller, and Ludwig (2017) compared the gaze behavior of of study participants using navigation systems with maps showing either reduced or abstract information. They found that an abstract interface leads to more visual attention on the environment than on the navigation system. The authors argue that navigators are faster in finding the way with abstract interfaces due to the abstract, yet relevant information for navigation. This study analyzed different digital designs but in an indoor environment. However, we still have a poor understanding of people's viewing behaviors during assisted pedestrian navigation in the real outdoor world.

Although mobile eye-trackers facilitate data collection in the real world, analysis of the data is challenging. Methods are quite far progressed under lab conditions with analog static maps but are not at the same level in the real-world environments with interactive maps (Blascheck et al., 2014). There are few methods for analyzing and visualizing the individual and dynamic data (Göbel, Kiefer, & Raubal, 2019). Very little research in outdoor navigation using eye-tracking has been conducted, because the annotation process of the recorded data is laborious due to individual walking speeds and viewing directions in a constantly changing spatio-temporal context (Goldberg & Kotval, 1999; Kiefer, Giannopoulos, Raubal, & Duchowski, 2017). Ooms, De Maeyer, and Fack (2015) identified problems with modern video recognition algorithms in analyzing eye-tracking data such as the constantly changing content of interfaces through map interactions, the appearance and disappearance of the map in the visual field throughout the video, and shadows and reflections that constantly change the device appearance. These changes prevent the algorithms from recognizing the map as the same feature throughout the video and hinders automatic detection of the area of interest (AOI) (Ooms et al., 2015). This often results in either manually annotating each gaze point (fixation) in the eye-tracking videos with only a small number of participants due to the laborious process (Koletsis et al., 2017; Liao et al., 2017; Ohm et al., 2017; Wenczel et al., 2017), or in segmenting the video to only analyzing parts of the whole recorded data (Kurzhals, Hlawatsch, Seeger, & Weiskopf, 2017). Research on methods to analyze spatio-temporal eye-tracking data have only been tested in lab environments with stable light conditions, little human locomotion, and small

numbers of participants (Göbel et al., 2019; Wolf, Hess, Bachmann, Lohmeyer, & Meboldt, 2018). However, it is important to accumulate participants with the analysis of eye-tracking data for statements on cognitive processes (Fabrikant, Rebich-Hespanha, Andrienko, Andrienko, & Montello, 2008). Methods to efficiently analyze gaze behavior during assisted navigation in real-world outdoor environments for a sufficient number of participants still need to be developed.

2.5 Summary

Navigation is an important human skill (Nazareth et al., 2019) which involves two key components: locomotion and wayfinding (Montello, 2005). Locomotion is actual bodily motion such as walking, which activates important brain areas for spatial knowledge acquisition and supports skill development for everyday activities. Wayfinding involves planning and decision-making tasks. Navigation assistance tools in the form of maps support these tasks (Wiener et al., 2009). With the technical developments of automation, navigation assistance changed from analog and static paper maps to digital and interactive maps on navigation systems.

Different levels of automation can be used to share tasks between a system and a human user who gets influenced in both positive and negative ways (Sheridan, 2002). Positive effects are, for example, the reduction of time-consuming, tedious tasks, and the feeling of being supported in achieving the task with the help of the system. Negative effects are passive behavior, a loss of power, and a degradation of skills for the human user when using automated systems.

In addition, automation in navigation assistance bestows positive and negative effects on humans (Ishikawa, 2019). Some of the positive effects include the fact that people can reach their destination quicker, have an allocentric representation of the environment to get an overview of the region, use GPS signals to facilitate self-localization and to receive location-based information, and change the scale and heading direction of the map to more easily match the information of the map to the environment and vice versa. However, there are also two major problems. First, the navigator changes from an active to a passive state during the task of wayfinding as they are handing over decision-making to the system. Second, the navigator changes their allocation of attention, such as attending to the GPS

signal on the navigation system instead of attending to the surroundings (Ishikawa et al., 2008). These changes have an effect on spatial knowledge acquisition during navigation system use (Parush et al., 2007). Below, I list the most important guidelines taken from these effects for navigation system designs (Willis et al., 2009).

- User-centered control and decision-making.
- Place-action associations between the environment and the navigation system.
- Information in short segments to enhance the allocation of attention to the environment and improve spatial knowledge acquisition.

This literature review indicates that there is a relationship between system design and human behavior, and also, therefore, with knowledge acquisition processes. However, it is unclear what kind of information a navigator ideally might need to get from a navigation system, and what form it will be in (Montello, 2009; Willis et al., 2009). Most of the studies have only studied wayfinding in laboratory environments without high ecological validity, although the research agrees that both components of navigation - locomotion and wayfinding - can influence cognitive processing (Appleyard, 1970; Gladwin, 1970; O'Mara, 2019). Walking, the basic form of human locomotion, should be part of any research studies on navigation as the human sensory inputs activate encoding processes for building a mental representation of the environment (Hegarty et al., 2006). Some research has been carried out on spatial knowledge acquisition during navigation system use, although very little research has been done on how these findings translate to designing systems that assist navigators in both a navigational task and spatial knowledge acquisition, as well as how, where, and when pedestrians should engage with a navigation system in outdoor environments to ensure spatial knowledge acquisition (Dai et al., 2018). It is inevitable that humans use automated assistance in navigation tasks, but it is also important that the design of automated navigation assistance promotes attention to the environment. This will ensure that humans remain part of their environment and develop healthy brains for everyday tasks (Lynch, 1960; Mondschein & Moga, 2018).

The analysis of eye-tracking data is well established in controlled lab and static desktop environments but still needs to be developed for interactive stimuli (e.g., navigation systems) and dynamic outdoor environments (Blascheck et al., 2014; Kiefer, Giannopoulos, Raubal, & Duchowski, 2017). The main reason to apply the method in the real-world environment is to confirm the evidence found for divided attention when using navigation assistance in lab environment (Gardony et al., 2013).

Below, I list the main research gaps identified in this chapter:

- Use-inspired research with both components of human navigation: locomotion and wayfinding
- Interplay between levels of automation in navigation systems and pedestrians' navigation behavior
- Relationship between navigation efficiency and spatial knowledge acquisition
- Empirical research on pedestrians' navigation behavior in real-world outdoor environments (e.g., map interactions, gaze behavior)
- Human interaction with location-based information and with their traversed environment

This thesis addresses the challenge of conducting outdoor experiments with pedestrians who use navigation systems and of observing their behavior during their navigation tasks. This methodological approach does not aim to develop a theoretical or computational model for assisted navigation but aims to conduct empirical studies under high ecological validity by systematically varying automated navigation assistance. The next section will describe this new framework.

Chapter 3

OVERALL METHODOLOGY

Only a few studies thus far have empirically examined partly automated navigation assistance and analyzed human navigation behavior in real-world environments. In this chapter[1], I first present the experimental framework to address the main research question on how the advantages of analog and automated navigation assistance can be combined to ensure navigation efficiency while increasing spatial knowledge acquisition. This chapter gives an overview of the methodology that applies to both empirical studies conducted within this thesis. The detailed methodology of each experiment (e.g., participants, procedures, stimuli) are detailed in Chapters 4 and 5.

This chapter is divided into four sections. First, I describe a novel experimental framework in detail which tests human navigation behavior and spatial knowledge acquisition in order to better understand the opportunities and implications of a use-inspired empirical study. Second, I show how levels of automation can be systematically implemented in navigation systems to understand the level of assistance a navigator should get from the system. Third, I describe the dependent variables of navigation behavior and how I measure them. Finally, I show how to add spatial information to mobile eye-tracking recordings, and how to spatially analyze map interaction data.

[1]This chapter contains parts from publications in connection with this doctoral thesis (Brügger et al., 2019 and 2016). A list of the publications can be found in Appendix A.

3.1 The WALK-AND-LEARN framework

In a real-world experiment, it is impossible to control for everything. Every participant will meet different conditions that influence navigation behavior and spatial knowledge acquisition. One outcome of such conditions is that data analysis becomes more challenging due to individual user behavior. However, the additional challenges of running studies in the real world are outweighed by the high ecological validity these settings offer (Kiefer et al., 2014). For example, a use-inspired scenario, which also takes place in the everyday life of the participants, ensures that the participants relate to the task, behave accordingly, and allow for authentic data collection. I will begin by explaining the framework in detail before showing the advantages and disadvantages of the WALK-AND-LEARN framework compared to traditional setups.

3.1.1 Two experimental phases

To ensure a use-inspired experiment for participants, and to better understand cognitive processes during navigation, I have developed a novel experimental framework to evaluate human navigation behavior and spatial knowledge acquisition. This experimental framework contains a learning and a testing phase and participants will be actively walking during both phases. Figure 3.1 depicts the proposed framework. **Phase 1** consists of an assisted route-following task. During this task, participants follow a route shown by the navigation system. All participants know that there will be a second phase of the experiment, but they do not know what this second phase consists of. Participants are not aware that acquiring spatial knowledge during Phase 1 is essential for succeeding in the second phase of the experiment. The spatial knowledge acquired during the first phase can be considered the result of incidental, rather than intentional, learning. **Phase 2** consists of an unassisted route-reversal task. During this task, participants have to retrace their exact same route back to the starting point by actively recalling their incidentally acquired spatial knowledge. This tasks is similar in procedure to a study by Karimpur, Röser, and Hamburger (2016), which was conducted in a virtual reality (VR) setting. An incorrect navigation decision at an intersection is considered as a navigation error and indicates insufficient spatial knowledge acquisition for the task.

3.1.2 Scenarios for both phases

Scenarios are important so that the participants can imagine the situation and behave accordingly. The scenarios for the WALK-AND-LEARN framework are taken from situations that many users of a digital navigation system have already encountered in their personal lives: they use a navigation system which then breaks down or runs out of batteries. In such a situation, people will then have to rely on their knowledge and experience to return to their starting point of their journey.

Therefore, for Phase 1, participants are first given a scenario where they have just left a bus at the starting point (blue pin in Figure 3.1) and that they have received a suggested route to a friend's home (black flag in Figure 3.1) shown on the map of their navigation system. Participants are asked to follow this route as quickly as possible, without running, and to use the navigation system as they would normally use theirs. For Phase 2, I told the participants that they have lost their keys during Phase 1, and they will have to retrace their exact same route to find the lost keys without using the navigation system because of a (fictitious) empty battery. This means that the participants cannot use any shortcuts in the route-reversal phase, even if they would have been able to find them. If they find the way back without any navigation errors (e.g., without wrong decisions at intersections), they will have acquired sufficient spatial knowledge during Phase 1. If they make a wrong decision at an intersection, then they have not acquired sufficient spatial knowledge during Phase 1 to find the way back. The detailed procedures of the two experiments are further explained in Sections 4.2.3 and 5.2.3.

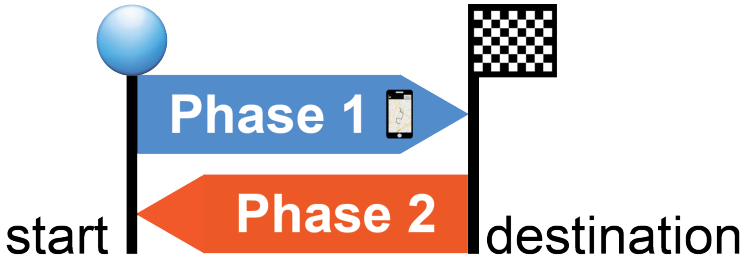

Figure 3.1: Experimental framework. Phase 1: Assisted route-following phase (incidental spatial knowledge acquisition) from start (blue pin) to destination (black flag). Phase 2: Unassisted route-reversal (spatial knowledge recall) from destination to start.

3.1.3 Advantages over traditional setups

Traditional setups of experimental user studies are very specific in terms of the types of knowledge they test to completely untangle influencing factors, but they are not directly transferable into a use-inspired manner. Use-inspired setups are important to ensure ecological validity because the interaction of the influencing factors is complex, dynamic, and unpredictable (Huang et al., 2018). I identified four advantages over traditional setups that I aim to address with this framework.

First, the WALK-AND-LEARN framework holds against the constraint of only using vision to learn and recall spatial knowledge as these studies are normally done in a lab or in a virtual environment. Traditional setups, such as lab environments, do not include actual human self-locomotion and do not activate all human senses (e.g., touch, hearing, or smell) during the navigation task. However, in everyday navigation tasks, humans might have used additional cues beyond the visual ones. One such example might even be a smelly trashcan on the sidewalk. With this proposed framework, participants can make use of all their senses to collect or recognize different clues such as landmarks that might help them to learn and recall the route.

Second, many experiments feature an active learning phase (e.g., moving through a given environment) and a passive, often abstract, knowledge testing phase (e.g., not actively moving through the learning environment). The testing phase can include tests such as image recognition tasks to assess landmark knowledge (Gale, Golledge, Pellegrino, & Doherty, 1990), images of intersections to evaluate route knowledge (Burnett & Lee, 2005), pointing tasks (Credé, Thrash, Hölscher, & Fabrikant, 2019), or qualitative sketch map drawing (Münzer, Zimmer, & Baus, 2012) to determine survey knowledge. These tests account for one type of spatial knowledge (e.g., landmark knowledge), allow for answers on paper or in a digital form, and typically test participants' acquired knowledge by means of visual stimuli. Showing participants images to test their landmark/route knowledge does not account for distances and timing of locomotion between landmarks/intersections compared to when testing their knowledge in-situ. When these "passive testing" tests are applied to a real-world study, problems arise that would not occur in virtual studies. Participants might never have encountered the view from the images; they might have chosen

different sides to walk along the street or may have crossed the street at different pedestrian crossings. The WALK-AND-LEARN framework does not allow for participants to walk in an unrealistic spatial context (e.g., walking in the middle of the street as it is often the case in lab and virtual environments), but it does allow for participants to walk where they want along the given route. The freedom to individually move in a real-world environment changes the egocentric view and experience of participants. The WALK-AND-LEARN framework (mostly) tests route knowledge without controlling for participants using other types of knowledge (e.g., survey knowledge acquired from the view of the navigation system during Phase 1) and does not allow for participants to (fully) use survey knowledge as they are not allowed to take shortcuts.

Third, traditional setups test participants in the same walking direction as during the learning phase. The application of this method in the real world is time-consuming, physically cumbersome, and challenging in terms of the organization of the experiment as participants have to be brought back to the starting point without acquiring additional spatial knowledge. However, the WALK-AND-LEARN framework does not demand time-consuming shifts of participants but does allow for smooth transitions between tasks and between the participants in a spatio-temporal context.

Finally, the novel framework allows participants to use the navigation system during Phase 1 as they would in everyday situations without any restrictions on map use. The framework allows us to collect data on map interactions based on real-world pedestrian behavior.

The WALK-AND-LEARN framework represents a novel, use-inspired approach to testing the participants' navigation behavior and spatial knowledge acquisition in a real-world environment with active tasks in-situ. Accordingly, two new research questions regarding the empirical framework will be also evaluated in this thesis:

> How valid is the approach from the empirical framework of an assisted and unassisted navigation phase for gathering useful data on pedestrian navigation behavior and spatial knowledge acquisition?

How well does the execution of an outdoor experiment work within the WALK-AND-LEARN framework?

Answering these questions will help to better understand advantages and to identify the limitations of such a framework over traditional setups (e.g., pointing tasks in VR). In summary, the WALK-AND-LEARN framework allows participants to have an active learning and testing phase in-situ, to use all their senses during both the learning and testing phases, to use navigation systems as they would in everyday situations, and to use their own chosen cues/landmarks to acquire and recall acquired spatial knowledge. However, we need to ask how we can systematically change the design of automatic navigation systems.

3.2 Stimuli: Map applications

The navigation system consists of a digital device with a base map and varying levels of automation within the navigational functionalities.

3.2.1 Digital device and base map

During Phase 1, the participants were given a Samsung Galaxy Tab S10.2 tablet with a topographic base map from Google Maps API as assistance (see Figure 3.2A). The test application was set to display a "north-up" street map and did not allow for switching layers (e.g., to a satellite image) to ensure that all participants used the same base map. However, participants could rotate, zoom, pan, and tilt the map according to their needs in order to provide an experience similar to that used on their personal devices. The test map would remain in north-up orientation and at the initial zoom level if participants chose not to interact manually with it. I added three visuals to the base map that were important for Phase 1 of the task: the starting point (blue pin), the destination (black flag), and the route (black line). Throughout this thesis, the digital device and the map application are referred to as "navigation system".

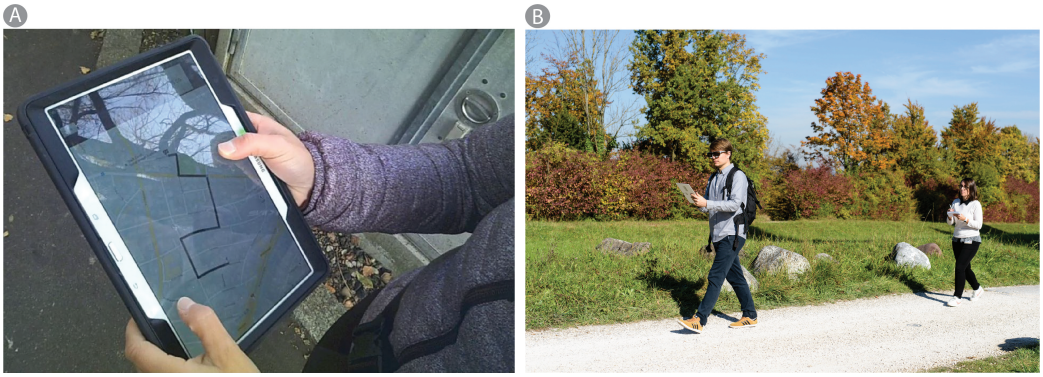

Figure 3.2: Experimental setup. Tablet with map application in use (A). A participant holds the navigation system (Phase 1 only) and wears eye-tracking glasses with an attached laptop in the backpack (during the whole experiment). The researcher follows the participant during both tasks and takes notes (B: Photo by Marc Latzel).

3.2.2 Levels of automation

In order to systematically vary levels of automation in navigation system stimuli, I used the approach depicted in Figure 3.3. The levels of automation (defined by Parasuraman et al., 2000, and listed in Table 2.1) build the basis for the chosen designs (Figure 3.3A). A low level of system automation indicates a high potential for human engagement, while a high level of system automation indicates low human engagement. For example, a cognitive process (abbreviated CP) relevant in navigation, such as self-localization, can be ranked in this scheme according to its automated specification and is shown in Figure 3.3B. Each cognitive process can be implemented with either a higher level of active engagement for the human (low level of automation) or a higher level of system assistance (high level of automation). The two colors indicate two different cognitive processes (CP1 and CP2) while CP1 is schematically depicted with two different levels of automation (low and high). The resulting navigation system designs are the assembled implementation of different levels of automation of the cognitive processes chosen for study (Figure 3.3C). This approach allows us to systematically implement automated cognitive processes in navigation systems. The specific cognitive processes and resulting navigation system designs will be reported in Chapters 4 and 5. The designs of the navigation system represent the stimuli of the individual experiments.

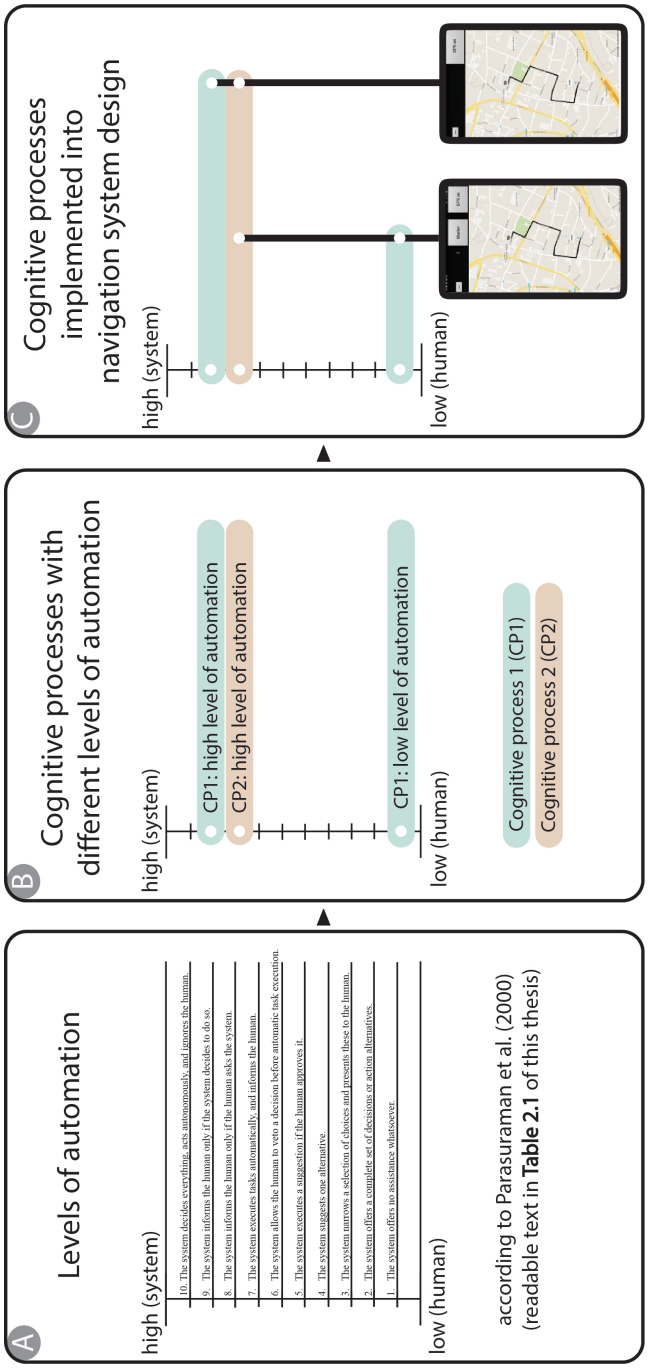

Figure 3.3: Schematic overview of the approach to navigation system design: Using the theory of levels of automation (A) to structure cognitive processes based on varying level of automatic execution by the system (B), and to combine and implement them in navigation system designs (C) to systematically analyze human navigation behavior with varying levels of system automation.

3.3 Measures of navigation behavior

I applied different methods to collect behavioral data, e.g., number and types of interactions with the navigation system and navigator's attention behavior (gaze data), on pedestrian navigation (independent variables). Most of the collected data include location-based, in-situ information and allowed for spatial analyses.

3.3.1 Navigation performance

In order to evaluate human navigation behavior, researchers suggested certain standard measures to measure navigation performance which included efficiency (time to task completion), the number of navigation errors, the number of stops along the route, and the number of interactions with the digital map (e.g., zooming) (Dillemuth, 2005; Janlert & Stolterman, 2017a; Meilinger et al., 2012; Spiers & Maguire, 2008). I collected data in two ways. First, I recorded where participants made errors by using pencil and paper. I took notes of the number of stops, hesitations along the route, and the time they took to complete both experimental phases. Second, the navigation system automatically recorded each interaction with the map in a log file during Phase 1 only, as the participants only used the navigation system during the first part of the experiment. Participants could freely zoom, rotate, pan, and tilt the map, or rotate the navigation system according to their needs, so as to provide a map use experience similar to that with their personal smart devices. The details of the digital map and the route characteristics are detailed in Sections 4.2.2 and 5.2.2.

3.3.2 Navigation errors: Indicator of insufficient spatial knowledge acquisition

One standard measure for navigation performance, navigation errors, was also used to determine spatial knowledge acquisition. During Phase 2, the participants had to walk the same route from the destination back to the starting point. If participants took a wrong turn at an intersection (decision point), I would call them back to the intersection and they would be given another chance to make the correct decision. The participants received explicit feedback similar to the study by Karimpur et al. (2016). Each wrong turn at an intersection was counted

as one navigation error and acted as an indicator of having not acquired enough spatial knowledge during Phase 1 to retrace the route. According to Gardony et al. (2013) and Willis et al. (2009), decreased spatial knowledge acquisition during assisted navigation is the consequence of a change in allocating attention to the environment. Therefore, studies interested in spatial knowledge acquisition should also consider allocation of attention as a cognitive process in the navigation system design, which I implemented in the experiment, and analyzed with the navigators' eye-tracking recordings.

3.3.3 Gaze behavior during navigation

To study the navigator's gaze behavior, I applied the physiological eye-tracking data collection method. As seen in Chapter 2, gaze behavior is an indication of cognitive function and visual attention (Duchowski, 2017; Goldberg & Kotval, 1999). Research with eye-tracking software during real-world outdoor navigation and interactive maps is still scarce, mainly because of the laborious annotation process for data analysis (Goldberg & Kotval, 1999; Kiefer, Giannopoulos, Raubal, & Duchowski, 2017), and because it is difficult to collect clean data. This is why participants wore mobile eye-tracking glasses (SMI-ETG) during both phases of my experiments. Sunshades and wind protection on the glasses reduced the potential (infrared) interferences and prevented the participants from squinting. This protection was added to ensure better data quality from the eye movement recordings. The glasses were connected to a laptop that the participants carried in a backpack. This laptop automatically recorded eye movements during the navigation experiment. Figure 3.2B shows the experimental setup with a participant holding a navigation system (i.e., tablet) and wearing a backpack with a recording device attached to the eye-tracking glasses (for privacy reasons, a friend of the researcher re-enacted the experimental scene).

3.4 Spatial analysis of navigation behavior

A strength, but also a challenge when analyzing human sensor data in wayfinding studies is the spatio-temporal context in which the data is collected.

To study temporal patterns of collected sensor data during a navigation task, researchers typically resort to statistical measures or graphs, such as timelines (Blascheck et al., 2014; Webber, Burnett, & Morley, 2012). One drawback of such data depiction can be the missing link to the traversed space where wayfinding happened. Various navigation studies have handled spatial segmentation in empirical analysis of navigation behavior differently, such as discretizing the route according to decision points (Javadi et al., 2017), regarding landmarks (Ohm et al., 2016), or route properties, such as pedestrian crossings or bike lanes (Trefzger, Blascheck, Raschke, Hausmann, & Schlegel, 2018). To date, there is no agreed-upon method on how to segment space to infer behavioral characteristics from large datasets, let alone a method grounded on principles derived from empirical data or analytical results. It seems clear that the segmentation of sensory data collected in a dynamic and continuous environment is critical. Therefore, I analyzed participant's interactions with the map using statistical measures and using a comparable spatial layout of a map. Visual indicators on a map help to identify behavior difference in space. Furthermore, I segmented the route for the analysis of the eye-tracking measures to make dynamic gaze behavior comparable between individual participants. These two indicators, visual and structural, will be explained in more detail.

3.4.1 Visual indicators for map interaction behavior

The map interactions of the navigators can be visualized according to their spatial distribution along the route. I therefore created icons that represent and distinguish types of map interactions (Figure 3.4) along the route. Four of the icons are independent of the navigation system, meaning that all participants could use the following map tools: zooming in (red), zooming out (yellow), rotating the tablet (green), and rotating the map (blue). Three of the icons are dependent on the navigation system design, meaning only some of the participants had the following map tools available, namely pushing a button to display their current location (dark blue), and allocating attention by humans (pink) or by the navigation system (orange). The group-dependent icons will be explained further in Chapter 4. Visualizing the icons on a map can help to reveal spatially dependent interaction patterns with the different interactive tools

available on the navigation systems rather than simply counting them along the timeline.

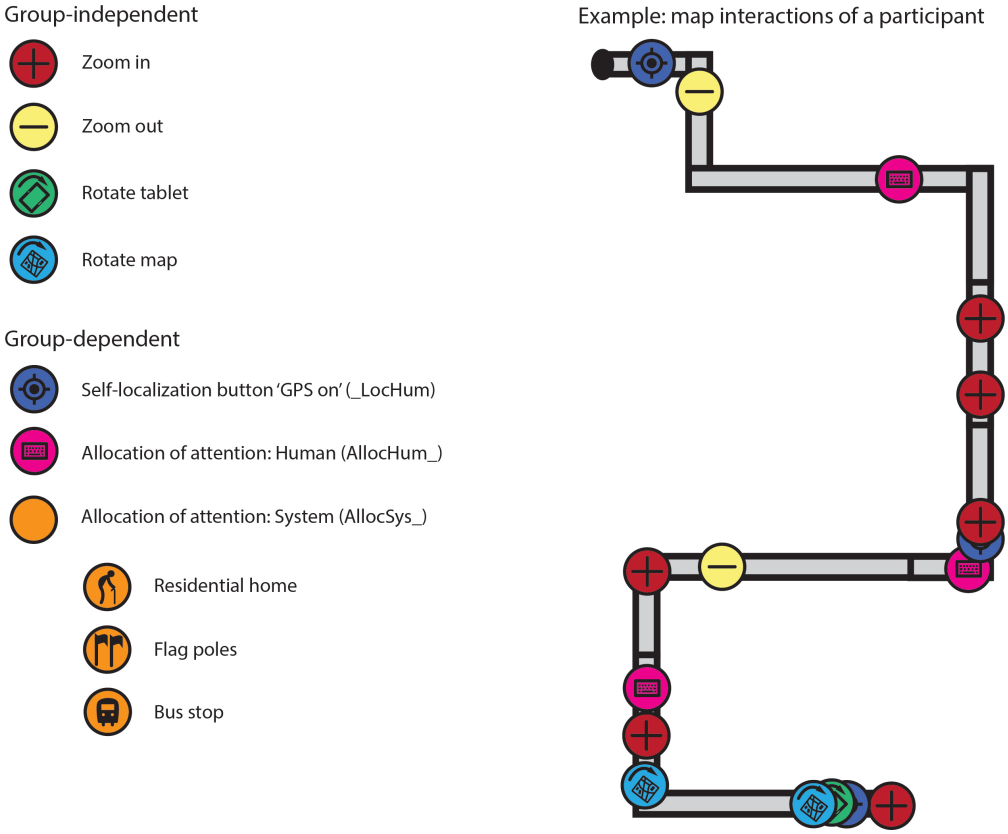

Figure 3.4: Icons for map interactions: The icons represent map interactions that will be put in a spatial context (example on the right) to analyze human behavior with map interactions during Phase 1 of both experiments.

3.4.2 Structural indicators for gaze behavior

The eye-tracking method in real-world studies yields huge amounts of fine-grained multimedia data (e.g., video, sound, gaze points, scan paths, human-system interaction data, etc.). The data are highly dynamic and are not comparable between participants or within the spatio-temporal context. The main problem with eye-tracking recordings is that the recordings do not (automatically) provide a direct geographic reference (i.e., two different participants might be at two different locations along the route after walking for

five minutes). This typically requires a great deal of tedious manual data post-processing to isolate the desired units of analysis. As a consequence, the sheer volume of this fine-grained, continuous temporal data stream might only have been partially analyzed due to time constraints and other technical limitations. For this reason, I chose to systematically divide the route into meaningful structural segments.

Spatial segmentation of navigation behavior

Segmenting the behavior data stream according to meaningful spatial elements in the environment enables us to take advantage of the entire recorded data stream, and to compare it across participants and across space.[2] The proposed approach will be explained in more detail below.

The first step in the eye-tracking analysis was to segment the data such that it allows for a comparison between participant behavior along the route. Therefore, I segmented the route at intersections that correspond to decision points for both experimental phases. Figure 3.5 shows, schematically, how to segment a route and depicts the end of a segment (S1), a full segment (S2), and the start of a segment (S3). Each segment features the navigation activity of approaching an intersection (yellow area) and the intersection itself (grey area) where a decision needs to be made. Each intersection is then followed by another segment.

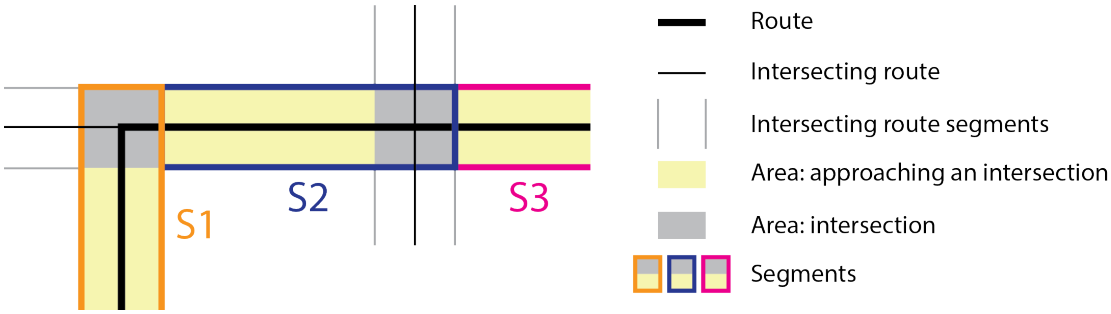

Figure 3.5: Schematic approach of spatial segmentation: A segment is defined by the spatial area adjacent to an intersection (yellow) and the area of the intersection (grey). The figure shows the end (S1) and the start (S3) of two segments along with one full segment (S2).

[2]This idea is part of the publication Brügger et al. (2018a). A list of the publications can be found at the end of this thesis in Appendix A.

Having schematically defined the route segments, I annotated the eye-tracking recordings using iMotions[3] software, using a duration dispersion-based fixation algorithm, with a fixation duration of > 100 ms. I watched the video recordings of each participant in order to identify the segment in the real world, and then annotated the screen videos of the eye-tracking recordings with the respective start and end positions for each segment. As a result, each fixation between a start and an end position of a segment using time stamp annotations is classified to a specific route segment. Statistical analyses of the participants then revealed spatial patterns of human gaze behavior within the same spatial context, and thus allowed us to focus on revealing the segments for deeper analysis. For this, I specified two eye-tracking measures: fixation duration and fixation location on the screen.

Eye-tracking measures

Each eye fixation included a duration which is one of the most central eye-tracking measures (Holmqvist et al., 2011). Longer fixation durations are associated with deeper and more demanding cognitive processing, and also with difficulty in extracting any kind of information (De Cock et al., 2019; Holmqvist et al., 2011). To reduce the heterogeneity of fixation durations within the segments for each participant, I calculated the mean fixation duration for each participant in each segment using the following formula:

$$\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

where $\bar{x}$ is the mean fixation duration in the segment, N is the total number of fixations in a segment, and x_{i} is the duration of fixation i in this segment.

Furthermore, each fixation has a location with X and Y coordinates on the recording video screen (i.e., 1280 x 960 pixels), as shown on Figure 3.6A. It is important to mention that the Y-axis for gaze location data is reversed so that higher values mean lower values in the vertical dimension. Fixation locations allow the identification of the position of the gaze within the video, and to classify potential horizontal and vertical shifts in gaze behavior. Higher values

[3]©iMotions 2019

for the Y-coordinate (lower in real-world vertical dimension) could indicate greater attention towards either the navigation system (up) or the pavement of the street to look out for obstacles (down). The direction between two subsequent fixation locations defines the direction of the saccade. Each saccade direction is classified into one of four classes: right up, right down, left up, and left down. Figure 3.6B shows an example of a fixation location on the screen video of a participant's first-person view. Comparing fixation duration, fixation locations, and saccade directions between groups allows us to reveal the gaze behavioral differences based on the navigation system design.

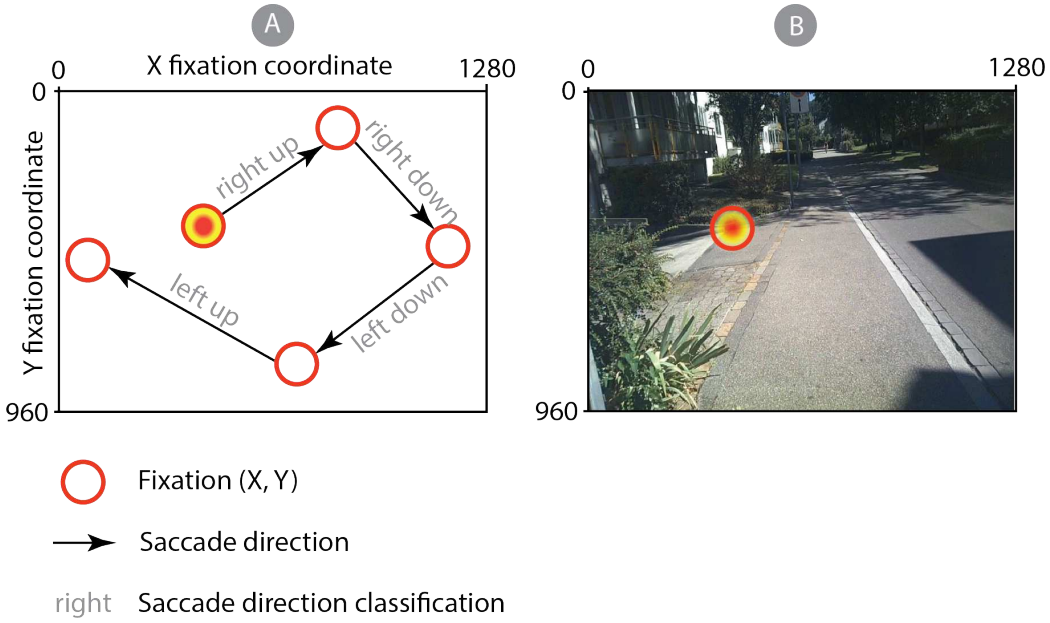

Figure 3.6: Schematic approach of fixation locations and saccade directions (A). An example of the video screen with the first-person view of the participant and the position of the corresponding fixation (B).

Eye-tracking analysis with spatially segmented navigation behavior

Adding the approach of spatial segmentation of the traversed route to, for example, the mean fixation duration, can reveal gaze behavioral differences between groups within the spatio-temporal context. Although these methods of gaze analysis do not reveal what the participant is looking at, they allow for efficient spatio-temporal analyses on human gaze behavior without the usual tedious manual work

of annotating each fixation to a specific AOI. The segmentation method allows the comparison of behavior differences across participants and across space. I also applied the conventional AOI annotation (e.g., gazes on the navigation system vs. on the environment) for the eye-tracking data recorded in Experiment 1, which are further detailed in Chapter 4. Additionally, the segmentation of the eye-tracking data can also be used to identify differences in walking speed along a route. The subtraction of the timestamp of the last fixation from the timestamp of the first fixation in a specific segment reveals the length of stay of a participant in a particular segment. The duration (in minutes) spent and the distance (in meters) walked per segment allow us to calculate walking speed in each segment for each participant during both experimental phases. The statistical analysis is explained in more detail in each experiment's methods section.

3.5 Summary

I have introduced the empirical WALK-AND-LEARN framework for use-inspired experiments in the real world involving two experimental phases:

- Phase 1: Assisted route-following phase assessing incidental spatial knowledge acquisition
- Phase 2: Unassisted route-reversal assessing incidental spatial knowledge recall

The framework presents advantages over traditional setups (see Section 3.1.3) in terms of in-situ experiences and use-inspired scenarios. Participants can use all their senses for spatial learning and their incidentally acquired knowledge is assessed in-situ. Participants can also use the navigation system as they would in everyday situations. Additionally, the procedure suggests allowing for smooth transitions between tasks and between participants.

The between-subject design consists of groups using navigation systems that are distinguished in cognitive processes in different levels of automation. Parasuraman's (2000) theory of levels of automation builds the basis for the design of the navigation systems that represent the stimuli for the experiments. The dependent variables measure navigation performance, individual navigation

errors as an indicator of spatial knowledge acquisition, and gaze behavior. I also constructed my visual-spatial data analysis approach based on visualized features (i.e. icons) and structural context (i.e. segments) along the navigated route to analyze and map human behavior in its dynamic spatial context. The new method of spatially segmenting behavioral data is part of the experimental framework and allows us to add spatial references to non-spatial raw data.

The next two chapters will describe the methods and results of the two experiments in more detail.

Chapter 4

EXPERIMENT 1

Based on the lack of experiments with pedestrians using automated navigation systems in real-world outdoor environments, the goal of Experiment 1 was to gain insights into how navigation systems with varying levels of automation can influence human navigation behavior and spatial knowledge acquisition in real-world, outdoor environments.[1].

4.1 Research question and hypothesis

Based on related work, I identified the following research question:

> How do varying navigation system designs (based on automated cognitive processes) influence navigation performance, spatial knowledge acquisition, map interactions, and gaze behavior during navigation tasks in a real-world, urban environment?

I hypothesize that the higher the total level of automation in a navigation system, the better the navigation performance, and the less spatial knowledge is acquired. Furthermore, I hypothesize that different navigation system designs can alter cognitive processing, which can affect map interactions and gaze behavior in ways that have not yet been studied.

[1]This chapter contains parts of publications related to this Ph.D. research (mainly from Brügger et al., 2019). A list of these publications can be found at the end of this thesis in Appendix A.

4.2 Methods

4.2.1 Participants

A total of 64 participants, who were mostly first-year students at the University of Zurich and the ETH Zurich, and who came from a variety of disciplinary backgrounds, took part in the outdoor experiment. Of the 64 participants, 44 were female (68%) and 20 were male (32%). The mean age of the participants was 25 years, ranging from 18 to 60 years (M=25 years, SD=8 years). The study was conducted in German, as all the participants were native German speakers. All except two of the participants owned a smartphone, thus they represent a sample with background knowledge of using mobile digital devices. Participants signed a consent form approved by the Department of Geography at the University of Zurich and were told that they could withdraw from the study at any time.

4.2.2 Materials

Study area and route characteristics

The study area was located in an urban residential neighborhood in Zurich's Oerlikon district, which is close to the University of Zurich but was unknown to the participants. The characteristics of the route are displayed in Figure 4.1, along with the base map from Google Maps[2]. The blue pin at the bottom of the map indicates the starting point and the black flag at the top of the map shows the destination, with the route highlighted in black. The route is approximately 800m long with a downward incline of 11m in total. The route consists of 14 intersections with different types of landmarks (buildings, parks, etc.) along the route, representing a typical urban residential environment. The route was chosen based on its variety of intersections, turns, and landmarks. All intersections are annotated with "I-" along with a number indicating their position along the route. The intersection annotations did not appear on the map display for the participants and are only added to allow reference to the intersections within this thesis. The route consisted of three right (I-3, I-7, I-13)

[2]©2016 Google

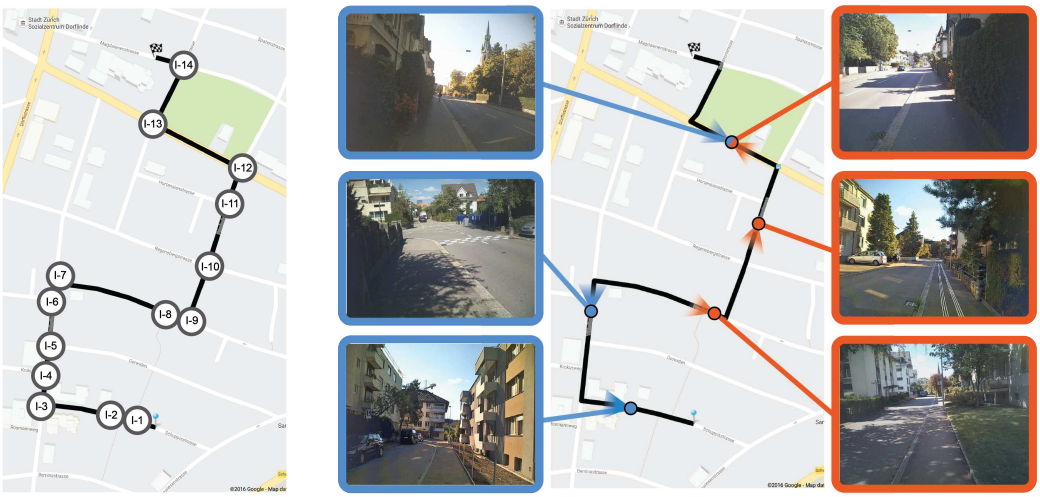

Figure 4.1: The route consists of 14 intersections (white circles) of which six are turns. Snapshots of the surrounding environment were taken at locations along the route (colored circles) in the walking direction (cones indicate viewing directions from those locations) for Phase 1 (blue) and Phase 2 (red).

and three left (I-9, I-12, I-14) turns in the walking direction from the start to the destination. The turns did not follow a regular pattern and divided the route into seven straight segments of varying lengths. In order to get an impression of the environment, three snapshots, each taken from an egocentric perspective for both empirical phases, are depicted in Figure 4.1.

Stimuli: Map applications

I applied a between-subject design by varying the levels of automation of two cognitive processes, which I accomplished by designing navigation systems that differed in their level of automation (i.e. navigation system design) according to the methodology introduced in Section 3.3. For this experiment, these variants combined two different cognitive processes - allocation of attention and self-localization - in two different modes. These cognitive processes and modes are motivated by the reviewed research on the role of attention during learning (Chrastil & Warren, 2012), the active learning hypothesis (Münzer et al., 2006), and the system solutions for cognitive problems Willis et al. (2009), as mentioned in Section 2.3.4.

The cognitive process "allocation of attention" (hereafter abbreviated as "Alloc") directs one's attention to certain features of the environment, such as a landmark (Chrastil & Warren, 2012; Richter & Winter, 2014). To address the cognitive problems of fragmentation of attention and the passive state of humans during assisted navigation (Willis et al., 2009), I will explain the two implemented modes in Figure 4.2.

- Figure 4.2B: The system (abbreviated "Sys") performs the process on its own, which means that the description of a certain landmark automatically appears as the user approaches the landmark, and automatically disappears as the user leaves the area around the landmark. The notification on the map consists of a marker symbol and a text description. The description automatically pops up without any user interaction (Figure 4.2B). The system vibrates for five seconds to make the user aware of the availability of this description and to make them attend to one of the three different landmarks (a residential home, two adjacent flag poles, and a bus stop) used in this study (see Appendix B.3 for the original and translated text). This mode corresponds to Level 9 "The system informs the human only if the system decides to do so" (Parasuraman et al., 2000), as shown in Table 2.1.

- Figure 4.2C and D: The system offers the opportunity for the human (hereafter abbreviated as "Hum") to type in some keywords that describe three self-chosen landmarks along the route. Participants could press a "Marker" button in the app (Figure 4.2C), which then allows them to type in a description (Figure 4.2D) of their current surroundings or some landmark within their field of vision. Participants could enter this description at three self-chosen locations along the route. This mode not only asks participants to make a decision regarding which landmark they wish to pay attention to but also asks what kind of text they want to add at the chosen location. The description is linked to the current position of the participant, but it does not actually appear on the map (i.e. the map does not change after performing this action). This mode corresponds to Level 1 "The system offers no assistance: human must take all decisions/actions." (Parasuraman et al., 2000) in allocating attention.

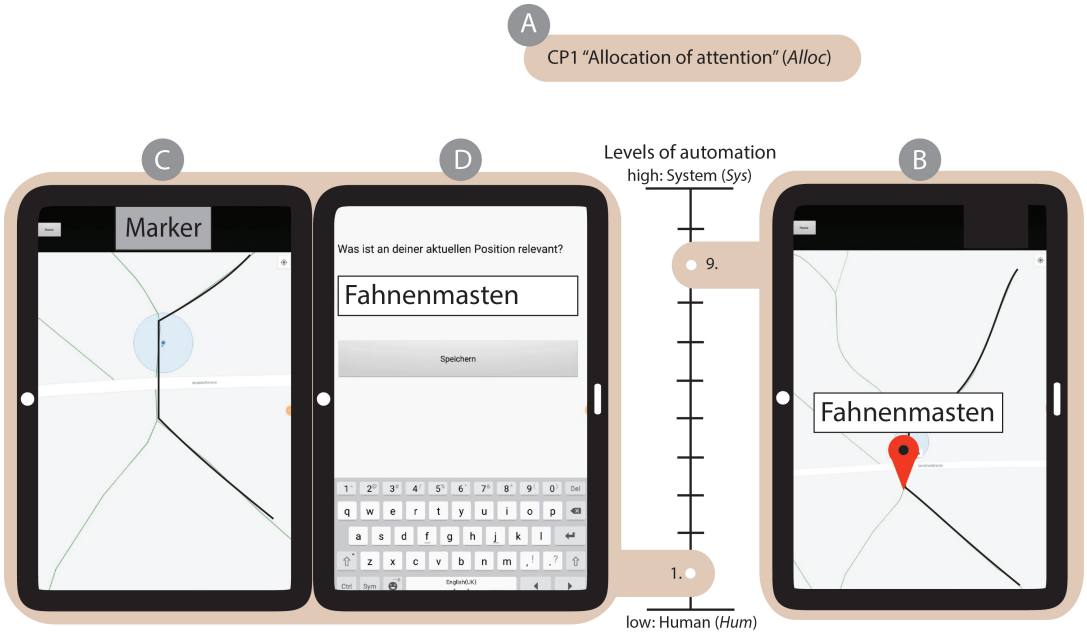

Figure 4.2: Implementation of the cognitive process of "allocation of attention" (A) with varying levels of automation (Levels 9 and 1). Either the system (B) or the human (C and D) allocates attention to landmarks in the environment.

The cognitive process of self-localization (hereafter abbreviated as "Loc") is the process of determining one's current location in relation to the environment by using visual clues (Meilinger et al., 2007). In Figure 4.3, I explain the two implemented modes in order to address the cognitive problems of fragmentation of attention and the lack of matching the information of the navigation assistance to the environment to self-localize (Willis et al., 2009).

- Figure 4.3B: The system (hereafter abbreviated as "Sys") performs the process on its own. This means that the location of the navigator is updated on the map as a blue dot and thus is permanently visible (Figure 4.3B). This mode corresponds to Level 10 "The system decides everything, acts autonomously, ignores the human" (Parasuraman et al., 2000).

- Figure 4.3C and D: The system provides the human with an opportunity to perform an action (such as pressing the "GPS on" button illustrated in Figure 4.3C) to display their current location on the map for ten seconds (Figure 4.3D), after which the blue dot disappears. This mode corresponds

to Level 8 "The system informs the human only if the human asks the system" (Parasuraman et al., 2000).

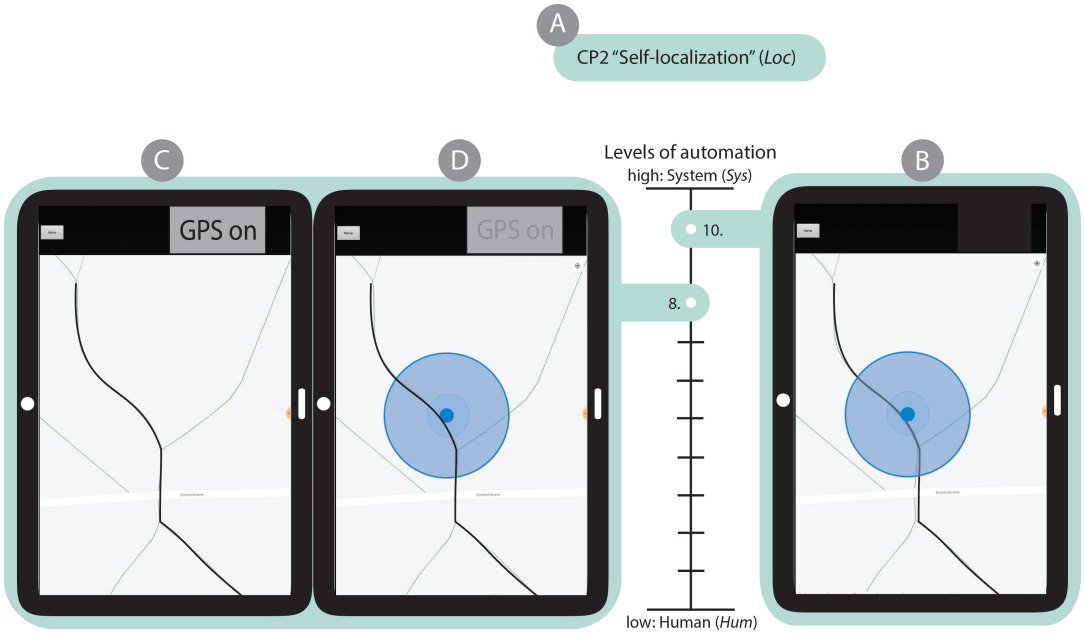

Figure 4.3: Implementation of the cognitive process of "self-localization" (A) with varying levels of automation (Levels 8 and 10). Either the system acts autonomously (B) or the human has to perform an action (C) to let the system execute the process (D) of self-localization.

Combining the two cognitive processes, each with one of the two implemented modes, resulted in four different navigation system designs that I tested (Figure 4.4). Each navigation system is associated with either a high level of active engagement on the human side and a low level of system automation (Figure 4.4 left, "Hum"), or a low level of active engagement on the human side and a high level of system assistance (Figure 4.4 right, "Sys"). Participants were randomly assigned to one of the four different navigation system designs, meaning that 16 participants used each application.

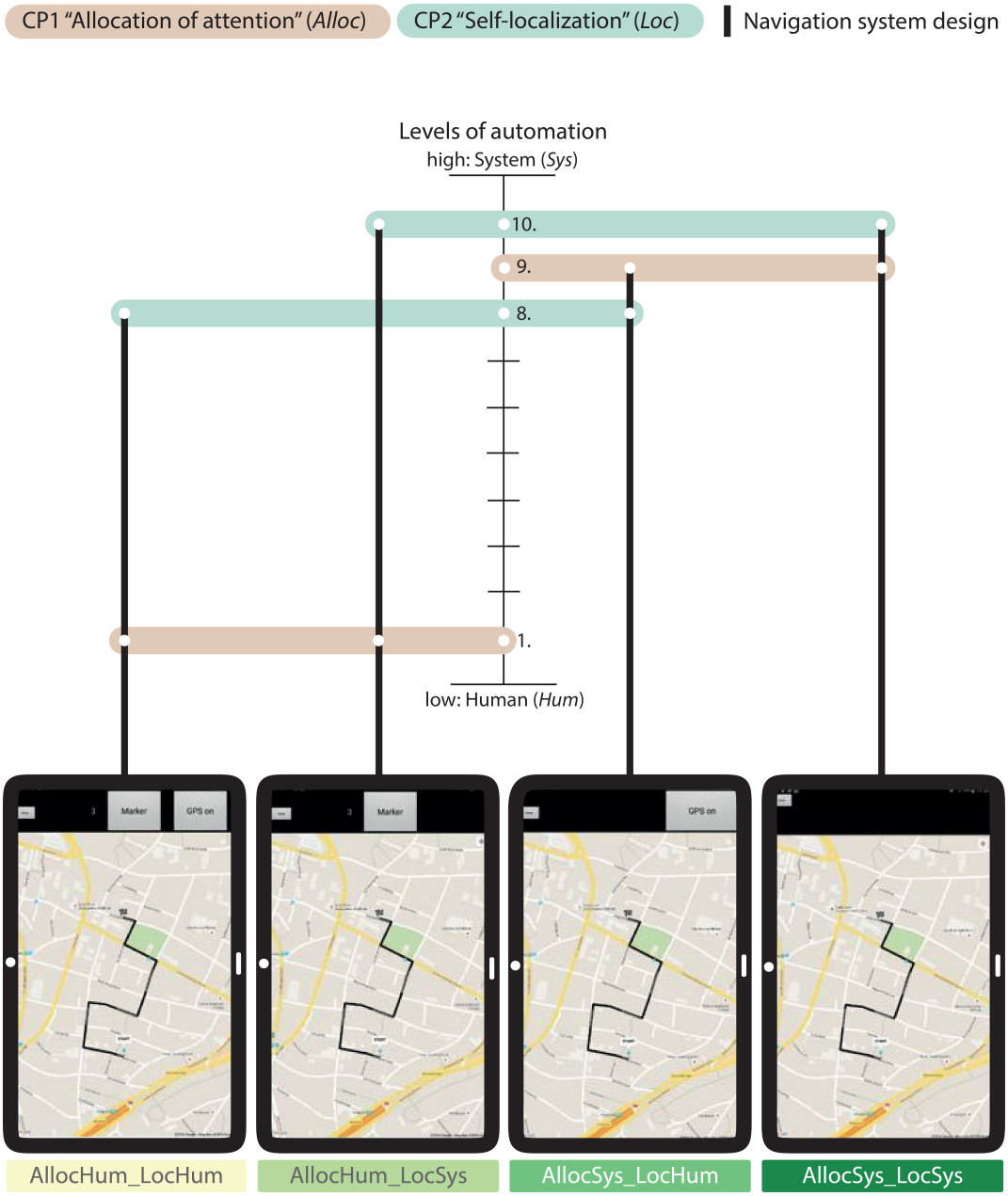

Figure 4.4: Four navigation system designs with varying levels of automation of the two cognitive processes of "allocation of attention" and "self-localization". Designs varied from little (left) to highly (right) automated cognitive processes performed by the system.

4.2.3 Experimental procedure

The experiment took place on non-rainy days between September to November 2016. If rain were forcast, I would cancel and reschedule the experiment because it was conducted entirely outside. Figure 4.5 illustrates the procedure for the experiment. Participants were asked to complete an online demographics questionnaire (Appendix B.1) and the self-assessment questionnaire *Räumliche Strategie* by Münzer and Hölscher (2011) in advance, at home. The questionnaire asked participants to rate their spatial strategies in terms of global-egocentric, survey scale, and cardinal directions. Münzer and Hölscher (2011) showed that these self-reporting measures can predict participants' spatial knowledge acquisition abilities. I sent an email to the participants the day before the experiment, reminding them to fill out the questionnaires if they had not already done so.

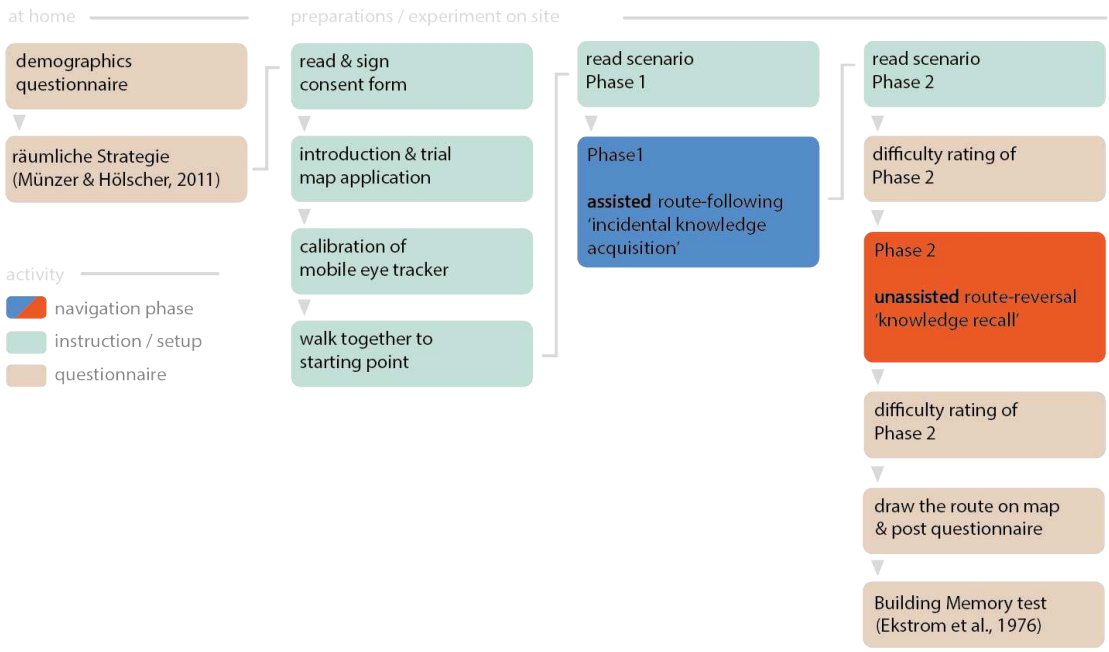

Figure 4.5: Experimental procedure including instructions, setups, and questionnaires. Phase 1 and Phase 2 of the empirical framework are highlighted in blue and red, respectively.

After arriving at the meeting point, participants were asked to sign a consent form and the procedure for the experiment was explained to them. Following this

introduction, I explained the randomly assigned navigation system design (one of the four applications depicted in Figure 4.4) to the participants, who could then familiarize themselves with the application during a training session. Next, I asked participants to don the eye-tracking glasses, whereupon I conducted a three-point calibration phase using the eye-tracking software iView. I did this by asking the participants to look at objects such as street signs that were between 7 and 10m away from them. Participants who wore glasses were asked beforehand (via email) to wear contact lenses if they wished to participate.

I would then lead the participants to the starting point of the test route where they were asked to read the instructions for Phase 1. The participants were first given a scenario whereby they had just left a bus at the starting point and that they had received a suggested route to a friend's house. The participants were then asked to follow this route as quickly as possible, without running. The two participant groups using the navigation system with a very low level of automation (measuring the cognitive process "allocation of attention") (Figure 4.4 left and second left) were additionally given the following instruction (translated from German to English): "On the way to your friend's house, you should write down three locations that are relevant to you for this route. The position at which this entry will be made is saved together with the text information and will be later integrated into the application. The entry is made when you click the 'Marker' button." Appendix B.4 lists the detailed scenarios for each group. Participants next received the tablet with a running application and were asked to perform the navigation task for Phase 1. I shadowed the participants from a 10m distance, taking notes on a paper pad about potential changes in the environment for each participant. This was necessary because the experiment took place in a real, dynamic urban environment.

After arriving at the destination, participants were given the instructions based on the scenario for Phase 2 (see Appendix B.4). I told the participants that they had lost their keys, and that they now had to retrace their exact same route without using the navigation system because their battery was "empty". This also meant that the participants could not use any shortcuts in the route-reversal phase, even if they had been able to find them. Each participant was then asked to subjectively rate the difficulty of Phase 2 on a Likert scale from 1 (very easy) to 5 (very difficult). The rating before the execution of this task provides a personal

assessment of the perceived difficulty of the task, independent of the participant's actual performance. Next, the participants were asked to reverse the route and walk unassisted (i.e. from memory) back to the starting point. Again, I shadowed the participants from a 10m distance. If participants took a wrong turn at an intersection (decision point), I called them back to the intersection where they were asked to make a new decision. Participants received explicit feedback (e.g., "You took the wrong turning. Come back and make a new decision") during their navigation performance, similar to the study by Karimpur et al. (2016).

After completing Phase 2, participants were again asked to rate the difficulty of Phase 2 on a five-point Likert scale (indicating perceived task difficulty) and to draw the route on a printed map (the same map as shown on the starting screen, but without the route and starting and destination points). This drawing would reveal the participants' ability to remember and to follow the route on an allocentric view of the environment. Participants were then asked to fill out an online post-test questionnaire (Appendix B.2) and to complete the *Building Memory test* (Ekstrom, French, Harman, & Dermen, 1976). This test would elicit an individual's ability to memorize the position of buildings on a street map, the result of which would indicate a participant's ability to memorize the landmarks on a map (survey perspective) used during Phase 1, which in turn may explain parts of their performance during Phase 2. I administered the test after the main experiment so as to not give away the memory component of the experiment (Phase 2), which might have influenced their learning behavior during Phase 1. At the end of the experiment, the participants received CHF 20 as compensation, signed a confirmation of receipt, and were thanked for taking part in the experiment. I also reminded participants to keep the experimental procedure confidential. The experiment lasted about 70 minutes on average.

4.2.4 Data analysis

As mentioned in Section 3.3, the dependent variables are navigation performance, spatial knowledge acquisition, and gaze behavior. I report the results according to the four groups of the between-subject design. All figures and tables follow the same order and color of the stimuli, "navigation system design," provided in Figure 4.4 (at the bottom). If an analysis involves the two experimental phases, they are

also highlighted in the corresponding colors (blue and red) as shown in Figures 3.1 and 4.5. All analyses are reported with a statistical test reported in text and visualized with boxplots (the black dots represent outliers), bar graphs, or maps. A result is statistically significant at a p-value of 0.05. I performed all analyses and visual outputs with R[3] and reported them according to the method suggested by Field, Miles, and Field (2012). I have either added descriptive statistics (mean and standard deviation) to the text or have referred to the values listed in Appendix B.6.

Mobile eye-tracking analysis

Unfortunately, I could only analyze 26 of the 64 participant recordings for both empirical phases due to calibration and recording issues. Given the small sample size in each group, I did not, therefore, run any statistical analyses on the eye-tracking data. For the post-task, eye-tracking data analysis in this experiment, I applied two methods.

The first method was where I segmented the route according to the schematic approach of spatial segmentation (introduced in Figure 3.5). Figure 4.6 illustrates the 13 segments for both empirical phases. Segments 1 and 6 have no sidewalk, Segment 2 has partial sidewalks on both sides, Segments 3, 4, 5, 6, 7, and 12 have one sidewalk (on the left during Phase 1), and Segments 9, 10, and 11 have sidewalks on both sides. If a street had a sidewalk on both sides, or on neither side, participants were free to choose a side to walk on. Therefore, I annotated the eye-tracking data according to this segmentation. To allow for comparisons between participants, I looked out for clear indicators along the route to define the start and end location of a segment. This was necessary for annotation reasons because some participants were looking at the navigation system in the video and only the sidewalk characteristics were visible as reference points as a result.

Additionally, I applied the conventional method of annotating each fixation to an AOI on a reference image. This was done with the Semantic Gaze Mapping tool provided by the SMI analysis software BeGaze. I applied two annotation analyses: egocentric viewing directions and divided attention between the environment and navigation system. First, I used a reference image with four

[3]www.r-project.org (access by 30/09/2019)

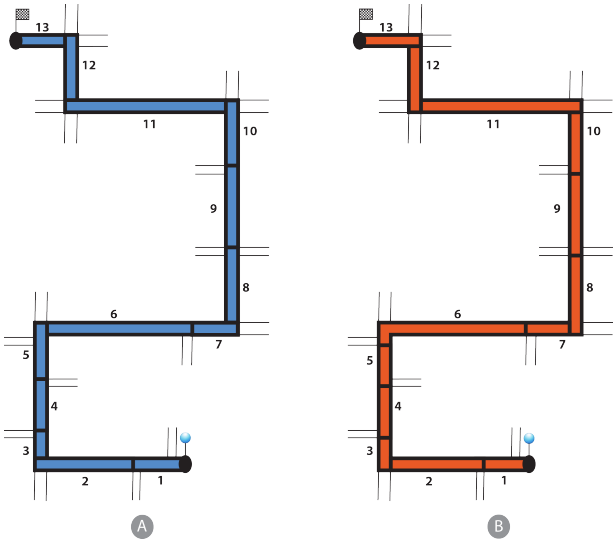

Figure 4.6: Spatial segmentation of the route for Phase 1 (A) and Phase 2 (B).

AOIs, delineated according to a participant's egocentric viewing directions (forward, backward, right, and left), in addition to fixations on the navigation system (Figure 4.7).[4] The navigation system AOI was only analyzed during Phase 1 as participants did not have access to the navigation system during Phase 2. This analysis should help to better understand gaze behavior in an egocentric viewing direction during the assisted and unassisted navigation phases. Due to the laborious work of annotating each fixation for both phases, I only analyzed the eye-tracking data of 15 participants (11 females, 4 males) for this analysis. Second, I used a reference image with only two areas of interest: the navigation system and the environment. For example, if a participant looked at the navigation system, I would annotate the fixation to the reference image "navigation system", and vice versa for the environment. This method was applied to eye-tracking data of 26 participants (six in the AllocHum_LocHum group, six in the AllocHum_LocSys group, eight in the AllocSys_LocHum group, and six in the AllocSys_LocHum group) during Phase 1.

[4]This figure and the corresponding analysis are part of the publication Brügger et al. (2018b). A list of the publications can be found at the end of this thesis in Appendix A.

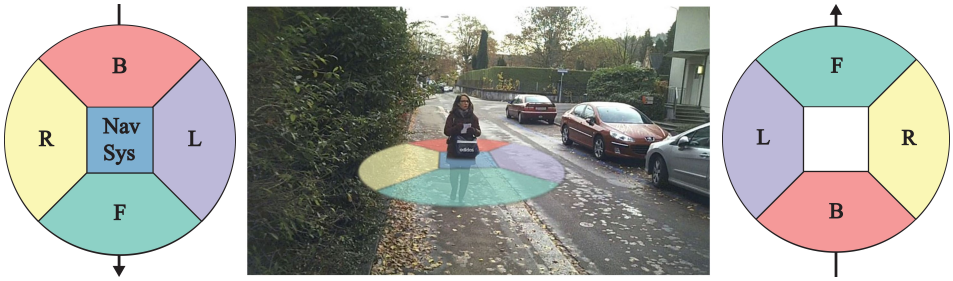

Figure 4.7: Reference images to annotate fixations in the egocentric viewing direction on a reference image (F: forward, B: backward, R: right, L: left) in both experimental phases (Phase 1: reference image left, Phase 2: reference image right) and the navigation system (NavSys) during Phase 1.

4.3 Results

I have reported all the results according to the four groups depicted in Figure 4.4 - the darker the color, the higher the levels of automation in the navigation system design. Each group consistd of 16 participants (11 females, 5 males).

4.3.1 Participants

Participants reported their frequency of using any type of map application on their digital system with a five-point Likert scale. Most participants (87%) used their mobile devices for navigational purposes several times a month. Apart from using digital map applications, I asked them to specify their experiences in mapping-related domains, such as map reading and cartography. The majority (80%) had experience in using map applications on a mobile device and in reading maps in general. In addition, the majority (60% to 70%) of the participants rated their experience with Geographic Information Systems (GIS) and with orienteering as little, or none. These results suggest a relatively homogeneous sample of participants in terms of map use in general and experience in using digital maps specifically.

The *Räumliche Strategie* questionnaire by Münzer and Hölscher (2011) reveals self-assessed spatial abilities in three different scales. The egocentric orientation scale evaluates how well a person knows directions and routes; the survey scale summarizes how well a person can build a mental map; and the cardinal direction scale assesses awareness of cardinal directions. Question 12 ("I am good

in remembering routes and finding my way back without problems") directly matches the second experimental phase. The scores range from 1 (I do not agree) to 7 (I strongly agree). The higher the scores, the better the participants can assess their ability. Overall, the results revealed that all three scales show a large range within all four groups (Appendix Table B.1). There are no significant differences in ratings across the groups for any of the scales (egocentric, $F(3,60)=5.12$, $p=0.525$; survey, $F(3,60)=0.604$, $p=0.615$; cardinal, $F(3,60)=2.13$, $p=0.106$) when tested with a one-way ANOVA. A Kruskal-Wallis test reveals that the ratings for Question 12 were also not significantly different between the groups ($H(3)=2.3191$, $p=0.508$). For the *Building Memory test* (Ekstrom et al., 1976), participants were asked to place buildings on an empty street map after studying the same layout with the buildings shown. A score of 0 was assigned if all buildings were placed in the wrong locations, while the maximum achievable score was 24 if all the buildings were correctly positioned. The higher the test score, the more buildings had been correctly located. Overall, the spatial memory scores of the participants were high (Appendix Table B.2) and a Kruskal-Wallis test revealed no significant differences between the four groups ($H(3)=0.9761$, $p=0.807$). The results of the spatial strategies and spatial memory tests indicate a homogenous distribution of spatial abilities across the four participant groups.

4.3.2 Navigation performance

In order to evaluate the participants' navigation performance, I analyzed four standard measures: time to task completion, interactions with the map, navigation errors, and the number of stops and hesitations along the route. None of the participants made any navigation errors during Phase 1.

Navigation efficiency

One of the advantages of automated navigation assistance is navigation efficiency (as shown in Figure 1.1). One aim of this experiment was to test whether a more active engagement of the human navigator with a navigation system (a lower level of automation) could be achieved without harming navigation efficiency. Figure 4.8 depicts the time taken to walk the route from the start to the destination for Phase 1, and from the destination to the start for Phase 2. For Phase 1, the time taken

to walk the route ranged from 7 to 12 minutes (Appendix Table B.3). A Kruskal-Wallis test revealed no significant differences in completion time between the four groups (H(3)=3.356, p=0.339). This result shows that different system designs did not affect the time it took for participants to complete Phase 1. For Phase 2, the time to walk the same route unassisted ranged from 6 to 13 minutes, with most participants returning to the starting point in less than 10 minutes. Again, a Kruskal-Wallis test revealed no significant completion time differences between the four groups in Phase 2 (H(3)=0.051, p=0.997). This means that being exposed to differing navigation system designs during Phase 1 did not significantly influence navigation performance without any navigation system assistance for the reversed route (Phase 2).

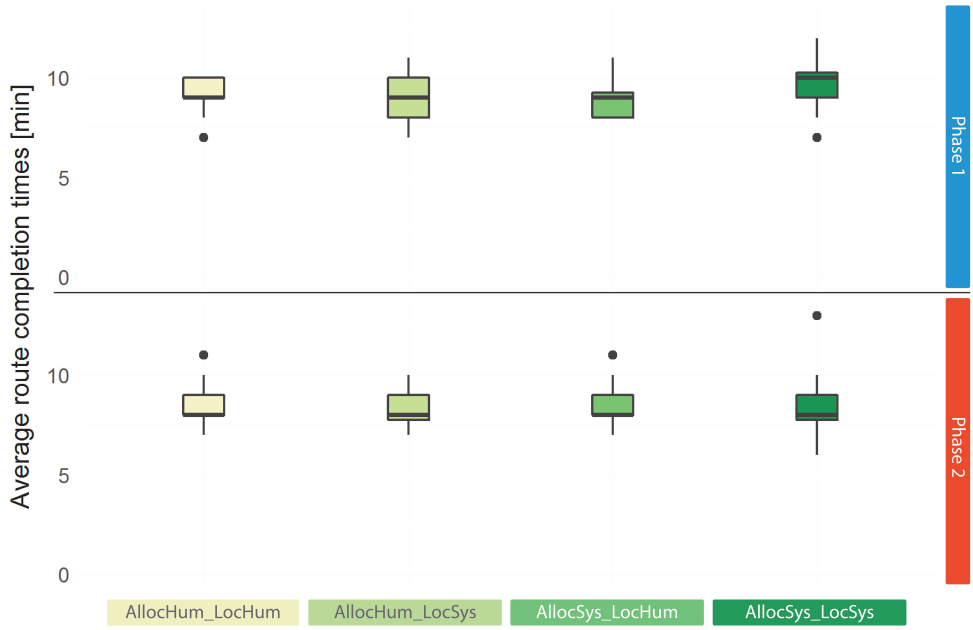

Figure 4.8: The boxplot shows that navigation system designs do not influence route completion times for Phase 1 or Phase 2. The values show the average time taken for walking the route.

Stops and hesitations

Stops and hesitations are also an indicator of navigation performance. Figures 4.9 and 4.10 show the number of times participants stopped or hesitated (slowed

down) along the route. A stop means that the participant has both feet on the ground and does not move in any direction, while hesitation is a clearly identifiable reduction in speed while continuing to move. The means and standard deviations of stops and hesitations across groups and phases are listed in Appendix Table B.4. During Phase 1, the two groups who allocated their own attention (AllocHum_LocHum and AllocHum_LocSys) stopped, on average, two to three times (to type the required keywords), but without harming their navigation efficiency, as shown in Figure 4.8. A Kruskal-Wallis test revealed significant differences in stops (H(3)=26.245, p<.001) and hesitations (H(3)=11.384, p<.01) during Phase 1, but not during Phase 2 (p>.05). All of the participants barely stopped moving during Phase 2. Each of the two groups who had to allocate their own attention stopped more often during Phase 1 than the two other groups (pairwise comparisons reveal statistical differences (p<.05). See Appendix Table B.5). However, the results did not reveal significant differences between the two AllocHum groups, nor between the two AllocSys groups (p>.05). Furthermore, the participants barely hesitated during Phase 1, although the AllocHum_LocHum group hesitated slightly more often than the AllocHum_LocSys group (H(3)=11.384, p<.01).

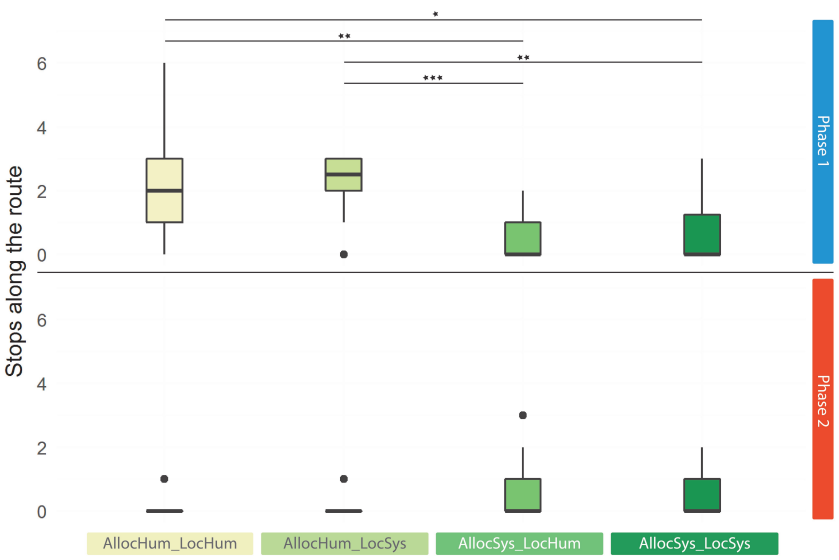

Figure 4.9: The boxplot shows small numbers of stops across groups for Phase 1 and 2. Significant differences are shown during Phase 1 across the groups (*p<.05, **p<.01, ***p<.001).

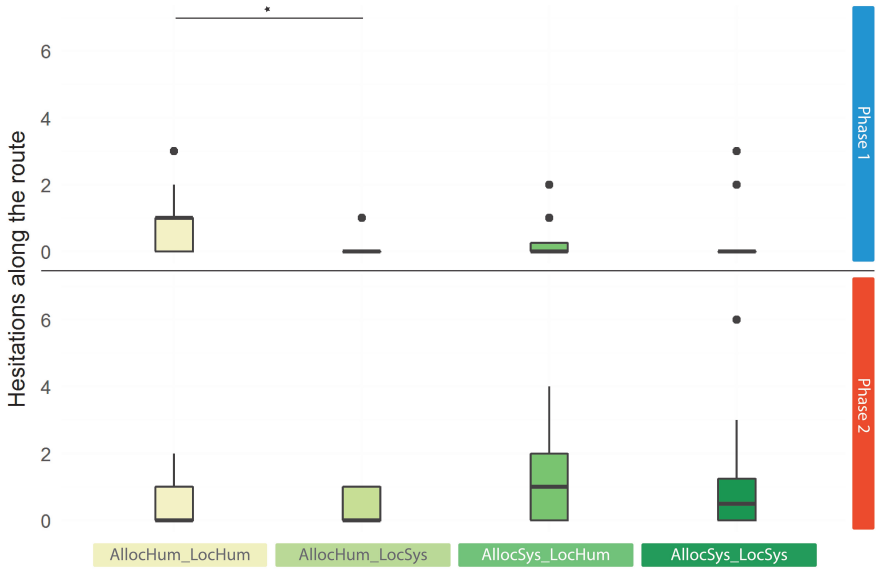

Figure 4.10: The boxplot shows small numbers of hesitations across groups for Phase 1 and 2. Significant differences are shown during Phase 1 across the groups (*p<.05).

Interactions with the navigation system and the map

Two out of the four groups (AllocHum_LocHum and AllocHum_LocSys) had the "Marker" button available for them to use. Figure 4.11 shows the locations along the route where the participants entered the descriptions in the system. The results show that many self-chosen landmarks are located at corners and at similar locations along the route. Interestingly, the two groups (AllocHum_) often also selected the first and third automatic markers (groups AllocSys_), namely the residential home (after Turn 1 at intersection I-3) and the bus stop (after Turn 4 at intersection I-12). One person even selected the exact three landmarks that the system displayed for the AllocSys_ groups. On the other hand, some participants found an interesting landmark right after the starting point and decided to allocate their attention there. Many participants waited until they were close to their destination to enter their third description of a landmark (e.g., the church) into the system. All the descriptions (the original text in German and their English translations) entered by the participants from the two AllocHum_ groups are listed alphabetically in Appendix B.5.

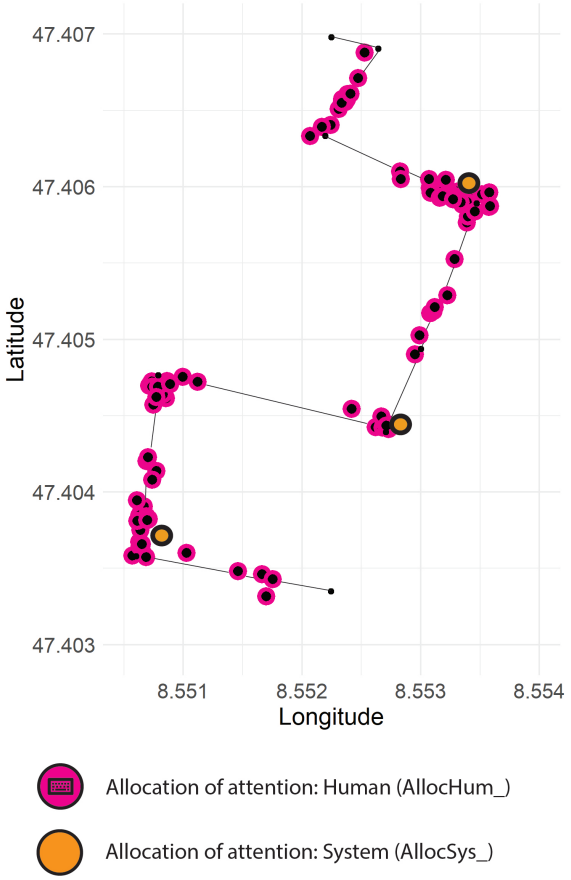

Figure 4.11: Locations along the route where participants from the AllocHum groups (pink) or the system from the AllocSys groups (orange) allocated attention to the environment.

Additionally, two out of the four groups (AllocHum_LocSys and AllocSys_LocSys) were perpetually shown their position on the digital map while navigating. The other two groups (AllocHum_LocHum and AllocSys_LocHum) had the option to display their current location on the map by pressing the "GPS on" button. On the one hand, pressing this button would distract the participant from attending to a navigated environment if it is unnecessarily used. On the other hand, this button could help to self-localize and reorient in the environment if used strategically. Figure 4.12 suggests that, on average, the AllocSys_LocHum group used the "GPS on" button more often than the AllocHum_LocHum group (Appendix Table B.8). A Wilcoxon test revealed no statistically significant differences ($W=33.5$, $p<.01$, $r=-0.51$). Also, the time

that the self-localization information was displayed was considerably higher for the AllocSys_LocHum group than for the AllocHum_LocHum group. The difference in duration is statistically significant (W=31, p<.05, r=-0.53 using a Mann-Whitney U test).

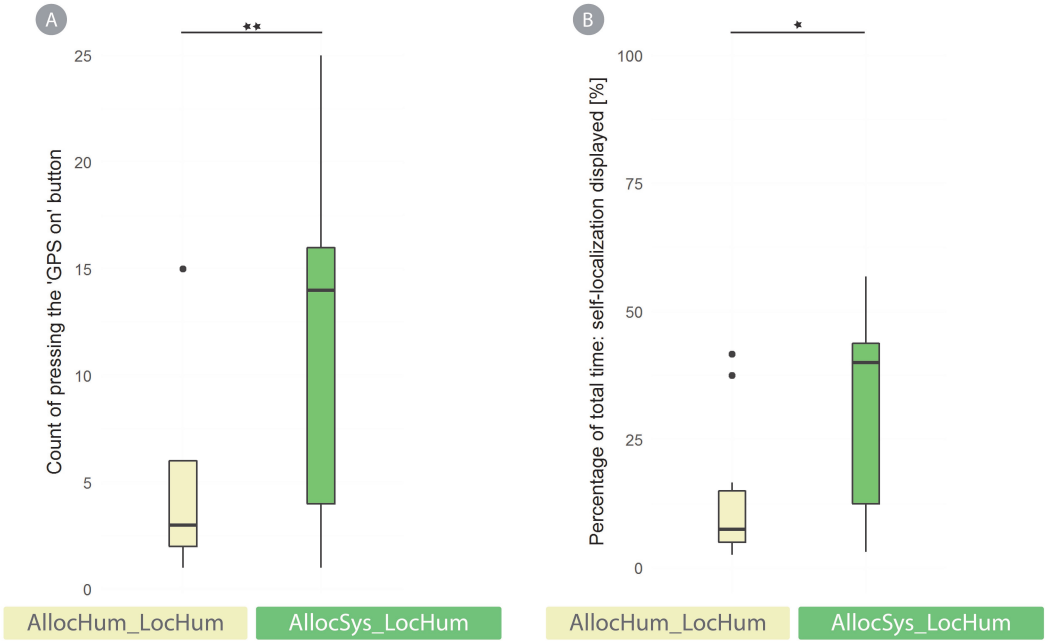

Figure 4.12: This boxplot shows significant differences in "GPS on" button use (A) and duration (as a percentage of the total duration of Phase 1) of available self-localization information on the digital map (B) between the two groups (*p<.05, **p<.01).

Each time a participant panned, zoomed, rotated, or tilted the map, the system recorded the type of interaction in a log file. Figure 4.13 shows all the interactions with the navigation system, aggregated across the four groups. Generally, some participants interacted frequently with the map display, while others hardly ever interacted with it (Appendix Table B.6). None of the participants used the tilt function. The AllocHum_LocHum group had the largest range of interactions, while the AllocHum_LocSys group had the smallest range, with one outlier. A Kruskal-Wallis test suggests that the amount of interactions with the navigation system significantly differs between the four groups (H(3)=18.166, p<.01). Pairwise comparisons of the mean ranks between groups revealed the significant differences between the AllocHum_LocHum and

AllocHum_LocSys groups, the AllocHum_LocHum and AllocSys_LocSys groups, the AllocHum_LocSys and AllocSys_LocHum groups, and the AllocSys_LocHum and AllocSys_LocSys groups (Appendix Table B.7).

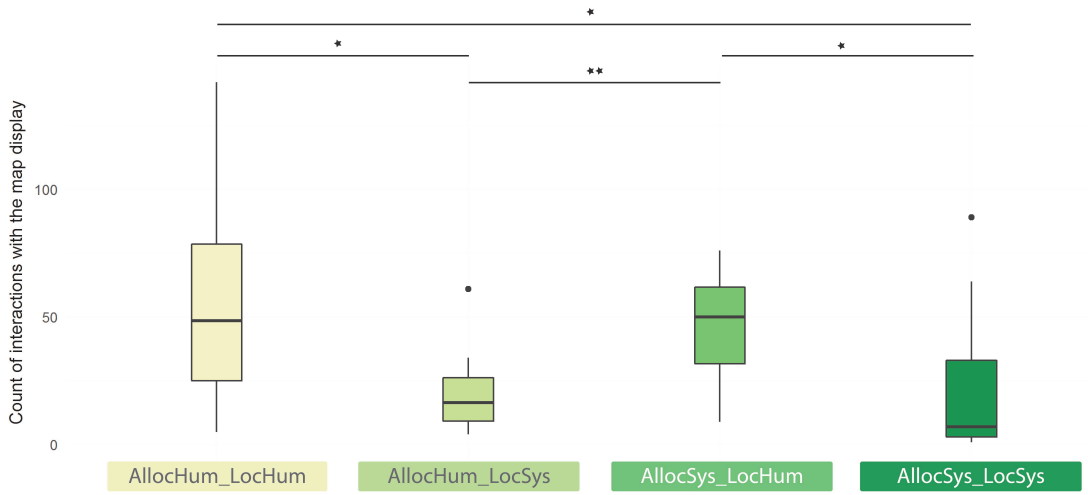

Figure 4.13: This boxplot shows significant differences in counts of interactions (zoom, rotate, pan) with the map display during Phase 1 across groups (*p<.05, **p<.01).

The spatial distribution of map interactions revealed clear spatial behavior patterns for each type of interaction. Each point on Figures 4.14 and 4.15 represents the center of the map. The red dot in the center represents the center of the map when the participants started the navigation system in Phase 1. Each dot represents a change in map view, and the location of the dot represents the center of the map after that change. The types of interaction indicate a change in the map based on information detail (zoom), orientation (rotation), or perspective (tilt). Figure 4.14 shows this spatial pattern of zoom levels. Google Maps stated in their API that street networks are visible at a zoom level of 15, and building details are visible at a zoom level of 20. Therefore, the lower the zoom level the larger the map scale (bright blue), and the higher the zoom level the smaller the map scale (dark blue). The results show that the larger the map scale, the more central the map center lies when taking the whole route (Start to Destination) into account, and the bigger the overview of the whole area is around the route. However, the center of the map is closer to the route when participants set the map to a smaller scale, indicating the need for more detailed

information at their current location. Two of the groups, AllocHum_LocHum and AllocSys_LocSys, showed a higher spatial density of smaller scales. At these locations, these groups needed more details from the map in order to navigate. The group with the lowest level of automation (AllocHum_LocHum) used the zoom function more than the other groups, while the group with the highest level of automation (AllocSys_LocSys) needed a smaller map scale (darker blue dots) when approaching the destination. Overall, the map centers are closer to the street with higher zoom levels and are more distant with lower zoom levels.

Another interaction is map rotation, usually performed to keep the top of the map in the walking direction after changing direction. The analysis of rotations only includes the map rotation and not the tablet rotation, as tablet rotation was not recorded in a log file. I gathered the tablet rotations from the video recorded by the eye-tracking glasses for some of the participants (used for the behavior type figures). Figure 4.15 shows the map rotation activities across the four groups. Again, each point indicates the map center of the activity. The values for the map rotations indicate the degrees in which the top of the map points clockwise from north. The AllocSys_LocHum group had the map centers during the rotation activities closest to the route compared to the other groups. Otherwise, the results of the rotation behavior revealed no clear spatial patterns. Furthermore, all participants from all the groups rotated the map in multiple directions. The third interaction with the map which needs to be analyzed is the tilt function. Tilting the map changes the viewing angle on the map and makes the map features appear in perspective: closer features appear larger and features in the distance appear smaller. Since only one person tilted the map once at the end of the route, I did not include the figure or result here.

Figure 4.14: Map centers are close to the route with a smaller map scale and are more distant from the route with a larger scale across all four groups. Small map scales (high zoom levels) at two locations along the route. The red dot indicates the initial map center. Data is from all 16 participants per group.

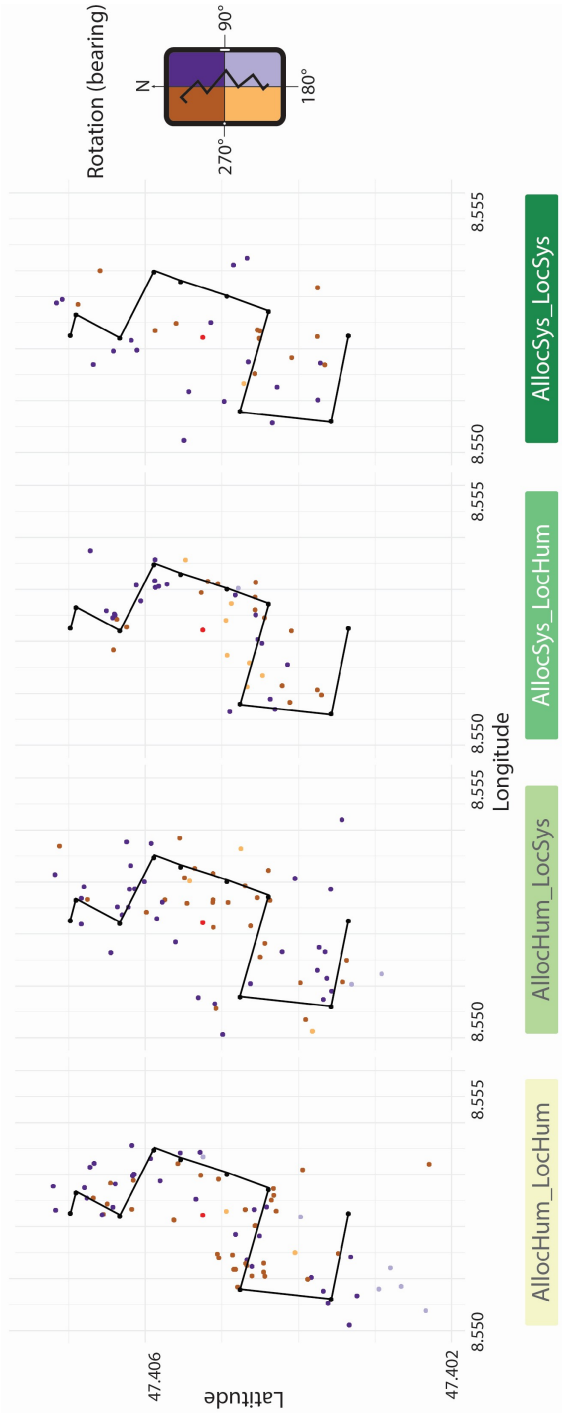

Figure 4.15: This figure shows no clear spatial pattern of rotation behavior across the four groups. All of the groups rotated the map in all directions. Data is from all 16 participants per group.

Overall, the spatial analysis of map interactions revealed that the participants changed the center of the map along the route while performing the route-following task. The map centers were spread between the streets of the subsequent route meaning at the inner part (not outer part) of the subsequent turn. The activity of panning the map is dependent on the types and levels of map interactions, and the varying level of automation (different navigation system groups). What is noticeable is that participants used the zoom at specific spatial locations (density of map changes to a smaller scale at intersection I-9 and close to the destination). This indicates the need for a more detailed map view at these locations to match the current location in the physical environment with the map information.

The use of interactive tools with a navigation system leads to different types of behavior. Webber et al. (2012) defined three strategy groups during navigation assistance use: navigators who constantly need support and information ("constant support and information"), navigators who use the device for tactical information and forward planning ("independent and attentive"), and navigators who hardly use the device for information and mainly use the GPS signal to confirm their location ("least effort and inattentive"). However, these strategy groups do not account for the different interactions with the map. Therefore, I categorized the participants' interactions with the navigation systems into five types of behavior (see list below). The zooming, rotating, and tactical behavior are similar to the "independent and attentive" strategy group posited by Webber et al. (2012), and the irresistible and constant behavior is similar to strategy group "constant support and information", again posited by Webber et al. (2012). Each participant can be categorized into more than one behavior type. For example, a participant can simply use the rotating tool while showing a constant behavior pattern. Figure 4.16 illustrates examples of the following behaviors along the route.

- Zooming behavior: Participant only used the zoom tools (zoom in and zoom out) at specific locations. Typical behavior includes zooming in and immediately zooming out again (Figure 4.16A).

- Rotating behavior: Participant only used the rotation tool (e.g., map or tablet rotation) at specific locations, such as after each turn (Figure 4.16B).

- Tactical behavior: Participant interacted with the navigation system infrequently but used multiple tools at specific locations (Figure 4.16C).

- Irresistible behavior: Participant used all interaction tools along the route without a dominant tool or spatial pattern for strategic use (Figure 4.16D).
- Constant behavior: Participant constantly used one interaction tool (e.g., the "GPS on" button) resulting in a regular spatial pattern along the route (Figure 4.16E).

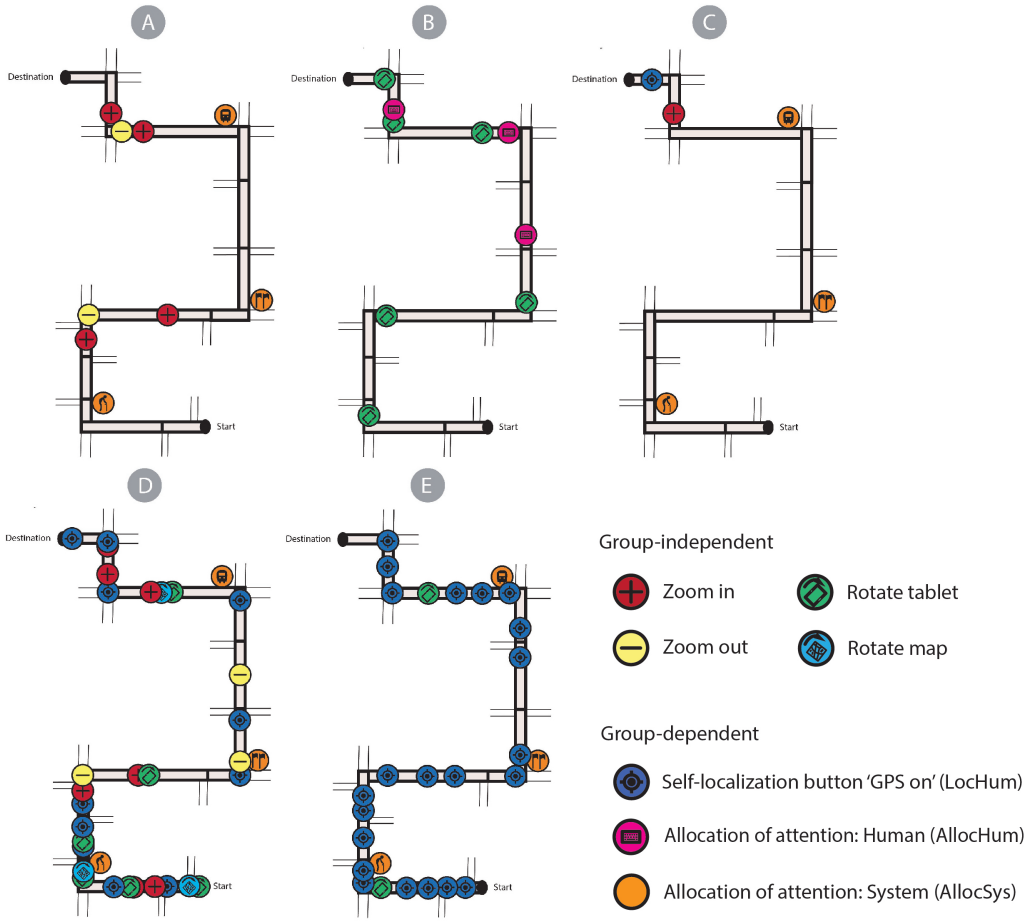

Figure 4.16: Examples of participants' behavior using map interactions: Zooming behavior (A), rotating behavior (B), tactical behavior (C), irresistible behavior (D), and constant behavior (E).

Interestingly, and independently of the navigation system, many participants could not resist using all of the interactive map tools and also used the map tools when they felt it was necessary (both tactical and strategic). The participants

who allocated their own attention (typing of keywords) used the zoom tools more often than participants who received system notifications. Additionally, the participants who constantly had the self-localization information available as a blue dot (AllocHum_LocSys and AllocSys_LocSys) were either rotating the tablet, the map, or both together more often than the participants who had the information on demand (those with the "GPS on" button). All participants in the AllocSys_LocHum group can be categorized into the "constant" behavior group because they constantly used one specific interaction tool. An example of such a participant is shown in Figure 4.16E. The different behaviors with the navigation system led to different experiences during Phase 1, which also had implications for Phase 2 of the experiment.

Rating of the difficulty

As Phase 2 of the WALK-AND-LEARN framework is a novel approach to assessing spatial knowledge, I was curious to know how the participants perceived the difficulty of this task. After the participants had finished Phase 1 and had read the instructions for Phase 2, they were asked to rate their perceived difficulty of the task "Finding the exact same way back without assistance" on a five-point Likert scale, ranging from 1 (very easy) to 5 (very difficult). They were also asked to rate the difficulty of the task again after completing their walk back, using the same scale. Overall, on average, the ratings were all below 3, thus indicating that the participants perceived the task to be relatively easy (Appendix Table B.9). The range of ratings is larger before, rather than after participants performed the route-reversal. The variation in ratings was very small for the AllocSys_LocSys group, meaning that participants in this group agreed more about the difficulty of this task both before and after Phase 2 compared to the other groups. All groups rated the difficulty of Phase 2 as easier after they performed it, compared to before. This indicates an overestimation of the task's difficulty in their first rating. A Kruskal-Wallis test revealed no significant differences in ratings before ($H(3)=3.6814$, $p=0.289$) or after ($H(3)=0.75636$, $p=0.8599$) performing Phase 2 across the four groups. The self-assessed task difficulty can then be compared with actual task performance (number of navigation errors).

4.3.3 Navigation errors: Indicator of insufficient spatial knowledge

I then tested the participants on how well they found their way back to the starting point with the navigation system. Because the participants were asked to retrace their exact same route to the starting point, each wrong turn at an intersection was counted as one error. Figure 4.17 summarizes the results for the different groups. In the two groups with more human-centered system designs (AllocHum_LocHum and AllocHum_LocSys), three participants (18%) made a wrong route choice at one intersection. In the AllocSys_LocSys group, six (37.5%) participants made at least one mistake during Phase 2. What is noticeable is that 10 out of the 16 participants (62.5%) in the AllocSys_LocHum group made the wrong navigation decision for at least one intersection. A Kruskal-Wallis test reveals that the mean error is significantly affected by the navigation system ($H(3)=8.4962$, $p=0.034$). However, it is important to mention that the number of errors was often zero, and was generally low overall. Nevertheless, the number of participants with a navigation error varied greatly between the groups (see the standard deviation values in Appendix Table B.10). The four participants with the highest number of errors (three) are in the two navigation groups using a navigation system that features higher levels of automation (i.e., lower active human engagement). More errors suggest that these participants were less effective in recalling their spatial knowledge of the route compared to the other participants, and indeed acquired less (accurate) spatial knowledge during Phase 1. In total, 12 participants made only one error and 42 participants made no errors at all, meaning that the majority of participants were able to effectively retrace their route. In order to better understand the differences in the navigation systems used during Phase 1, and the navigation errors during Phase 2, I analyzed the participants' gaze behavior.

4.3.4 Gaze behavior

I will next report the results of the eye-tracking analysis with three approaches resulting in diverse findings of gaze behavior in real-world environments:

- The traditional analysis method AOI: Differences in egocentric viewing directions between Phase 1 and Phase 2.

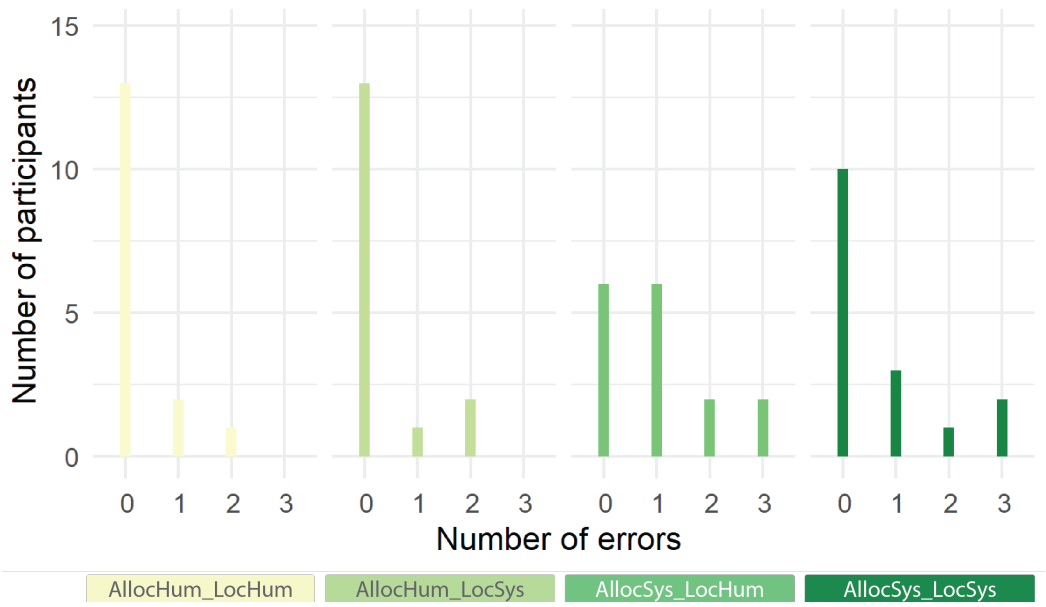

Figure 4.17: The number of participants and the number of errors (indicator for insufficient spatial knowledge acquisition) made during Phase 2.

- The new method of "spatial segmentation": Differences in spatial patterns of fixation durations and fixation locations between groups and experimental phases.

- A combination of both of the above-stated methods: Spatial variations of fixations on the navigation system.

Figure 4.18 shows the mean percentage of fixations in egocentric directions (forward, backward, right, left) during both experimental phases. During Phase 1, the navigation system is an additional feature in the environment that participants could fixate on, and the results showed that participants from all groups mainly looked in a forward direction (>50%) or at the navigation system (30%-37%). The highest number of switches between areas of interest therefore happened between the forward direction and the navigation system. During Phase 2, most fixations were in the forward direction (>85%). Surprisingly, no other egocentric direction attracted the participants' attention as much as during Phase 2. This result shows that the navigation system mainly reduces fixations in the forward direction (field of view of ±45° in the walking direction)

independent of the levels of automation in navigation systems. This could be an indicator of where a navigation system should allocate a human's attention. The fixations in the right, left, and backward directions increased slightly in Phase 2 compared to Phase 1, with most switches occurring between the forward, left, and right sides. This result is based on data that comes from the laborious process of annotating each fixation to an area of interest of a reference image. Therefore, the new method of spatial segmentation aims to reveal the possibilities and limitations of analyzing gaze data without exactly knowing where the participants were looking, or what they were looking at.

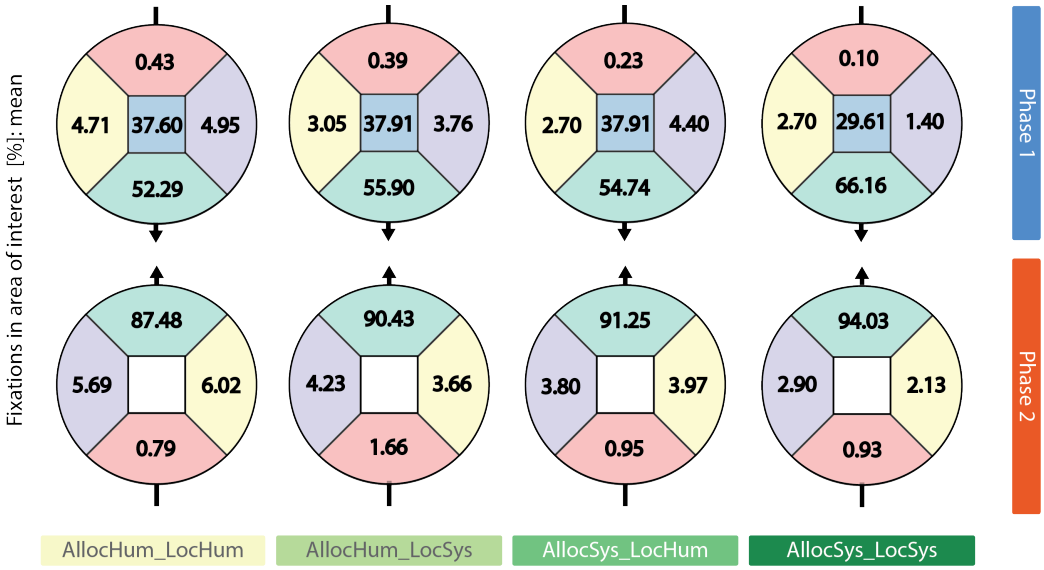

Figure 4.18: Mean fixation percentages in four egocentric directions (forward: green, backward: red, right: yellow, left: purple) and the navigation system (blue) during both experimental phases across the four groups. Graph according to Figure 4.7.

The new method of segmenting a route and annotating the gaze data with the segment borders (for a description of the approach, see Section 3.4.2) reveals interesting temporal and spatial patterns. Figure 4.19 shows the mean fixation durations for each segment during both phases and across the four groups. For each participant the walking direction was from Segment 1 to Segment 13 in Phase 1 (i.e. read the graph from left to right) and from Segment 13 to Segment 1 in Phase 2 (i.e. read the graph from right to left). What is immediately apparent is that generally, for all groups, the mean fixation duration during Phase 1 (the assisted route-

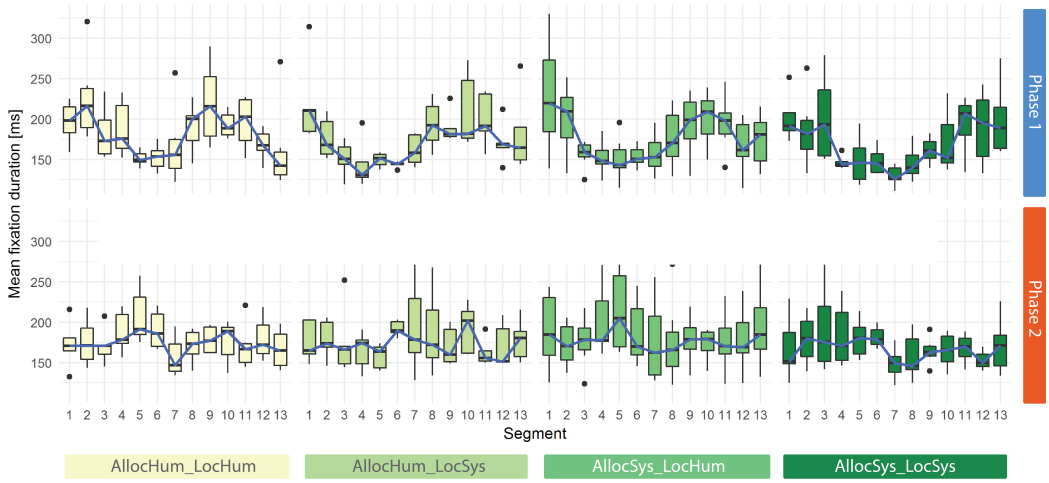

Figure 4.19: Mean fixation duration in each segment of the route across the four groups for Phase 1 and Phase 2.

following) follows a wave pattern that starts with longer mean fixation durations in the first segments of the route, followed by segments with shorter mean fixation durations, before again having segments with longer fixation durations toward the end of the route. This wave pattern seems to be independent of whichever navigation system is employed. During Phase 2 (unassisted route-reversal), this wave pattern is not identifiable anymore and changes across the groups. Here, no clear pattern emerges, and the mean fixation durations show large variations. Interestingly, the pattern of the AllocSys_LocHum group was inverted during Phase 2 compared with Phase 1. It turns out that there are no differences between the four navigation system designs, but there are distinct differences in the fixation duration patterns that emerge between the two experimental phases of incidental knowledge acquisition (Phase 1) and knowledge recall (Phase 2). Therefore, I can conclude that the difference in mean fixation durations depends on whether the participants are using a navigation system, not on the different designs of the navigation system.

Once I segmented the gaze data, it was possible to analyze variables other than fixation duration, such as fixation positions on the screen camera. I found distinct behavior patterns of fixation positions. Figures 4.20 and 4.21 show that the mean fixation position Y coordinate (vertical: up and down) is more dynamic across time and space than the mean fixation position X coordinate (horizontal: right and left). In particular, the AllocSys_LocHum group (which was the worst-performing group during the route-reversal task) shows a reverse behavior pattern in the vertical (Y) dimension during the experimental Phase 2 compared to Phase 1. The other groups also reveal differences in fixation positions in the vertical dimension between the street segments but do not reveal a similar or reverse pattern between the phases. If participants only looked straight ahead (and not left and right), as Figure 4.18 showed, the coordinate in the horizontal direction (X) would not change much. However, the results shown in Figures 4.20 and 4.21 revealed relatively stable median values in the horizontal direction (X coordinate). The analysis reveals a systematic change of "looking in the upper and lower part of the screen video" behavior (based on the fixation position in Y coordinate) with different navigation systems, while keeping the horizontal field of view in the center of the screen.

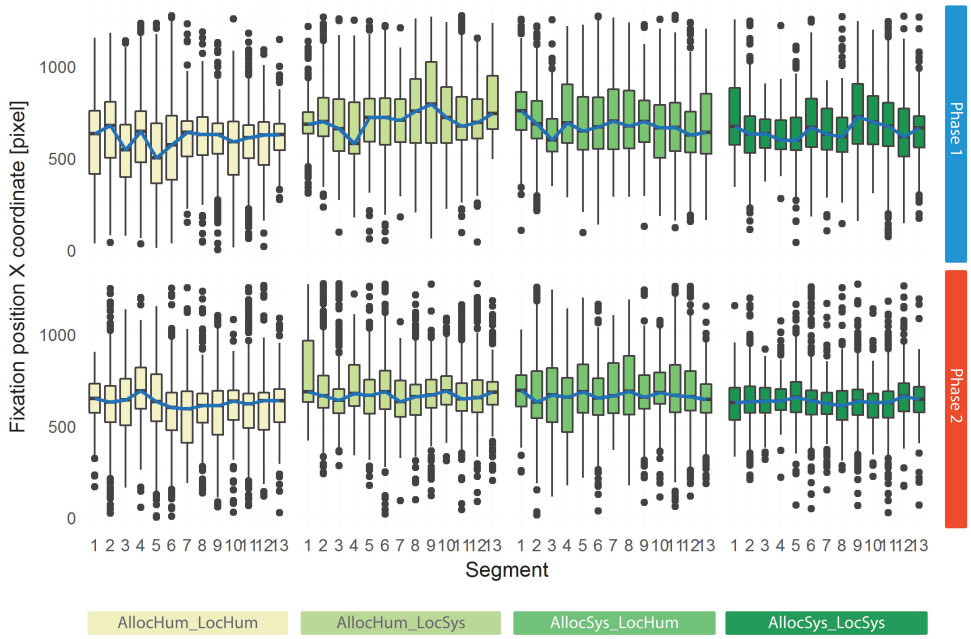

Figure 4.20: Fixation position in the horizontal (X) dimensions at the screen video camera in each segment of the route across the four groups for both phases.

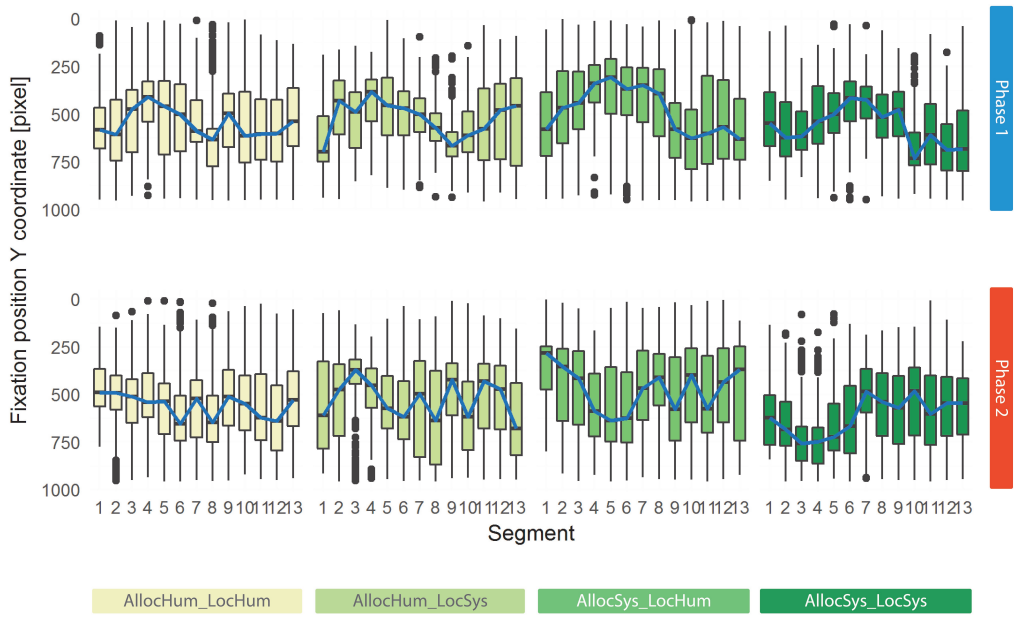

Figure 4.21: Fixation position in the vertical (Y) dimensions at the screen video camera in each segment of the route across the four groups for both phases.

Based on the fixation coordinates, I also visualized the saccade directions. Figure 4.22 reveals the distribution of saccade directions per group for both phases. The patterns of the two groups on the left (AllocHum_LocHum, AllocHum_LocSys) and the one group on the far right (AllocSys_LocSys) reveal similar behavior of subsequent fixation directions in all four saccade classifications. However, the AllocSys_LocHum group behaved differently. Although the result is difficult to interpret, it shows different behavioral patterns of one of the navigation system groups in terms of saccade directions.

It is important to mention that none of the results of the fixations in egocentric directions, fixation durations, the fixation locations, and saccade directions include what people look at around them or how their head is positioned. This means that participants could have looked up at the sky with their head tilted backward, which could result in high Y coordinates, and the data would still not reveal this strange behavior. However, the analyses show us different gaze behaviors across groups and experimental phases.

To determine the division of attention toward the navigation system and the environment across space and groups, I also manually annotated the whole dataset with the reference image of two AOIs: the navigation system and the

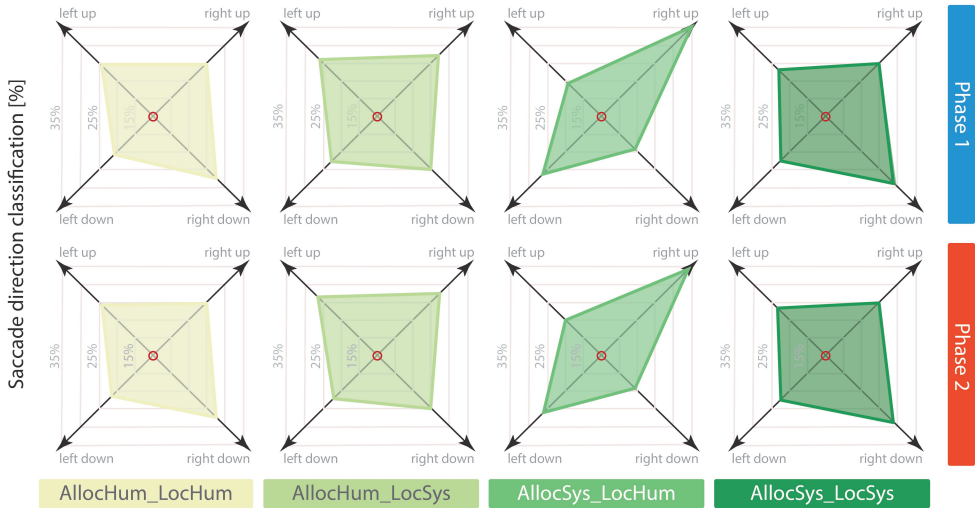

Figure 4.22: The classification of saccade directions based on horizontal (right and left) and vertical (up and down) changes of subsequent fixations across the four groups for both phases.

environment. Figure 4.23 shows the percentage of fixations on the navigation system during Phase 1 for the 13 segments across the groups. Fixations to the environment add up to 100 percent, and the fixations on the navigation system changed across segments and groups. All groups show the highest percentage of fixations on the navigation system in the first segment. This is unsurprising, as the participants had to orient for the task of Phase 1, particularly as Segment 1 covers a very short distance. Interestingly, the groups who typed in some keywords (AllocHum_LocHum and AllocHum_LocSys) show local maxima in the segments that include an intersection that is also a turning point (Segment 3, 5, and 7). The two groups with the notifications (AllocSys_LocHum and AllocSys_LocSys) show higher percentages of fixations on the navigation system where the notifications appeared on the map (Segments 3, 4, 7, and 10). This result of different viewing behavior on the navigation systems shows that it is possible to guide a human's gaze with varying levels of automation in navigation systems.

For the final analysis with eye-tracking data and the method of spatial segmentation, I was able to calculate the participants' walking speed from the eye-tracking data. Most segments revealed little variation in walking speed (Figure 4.24), although Segments 1, 7, and 13 showed a greater range of walking

speeds. The smaller the distance of a segment in the real world, the bigger the influence of fixations within this small segment, and the bigger the influence of duration on walking speed. The two groups on the left (AllocHum_LocHum and AllocHum_LocSys) varied their walking speed along the route during Phase 1, whereas the two groups on the right showed a more consistent walking speed, except in the starting and ending segments. During Phase 2, the walking speeds along the route were more dynamic across all the groups.

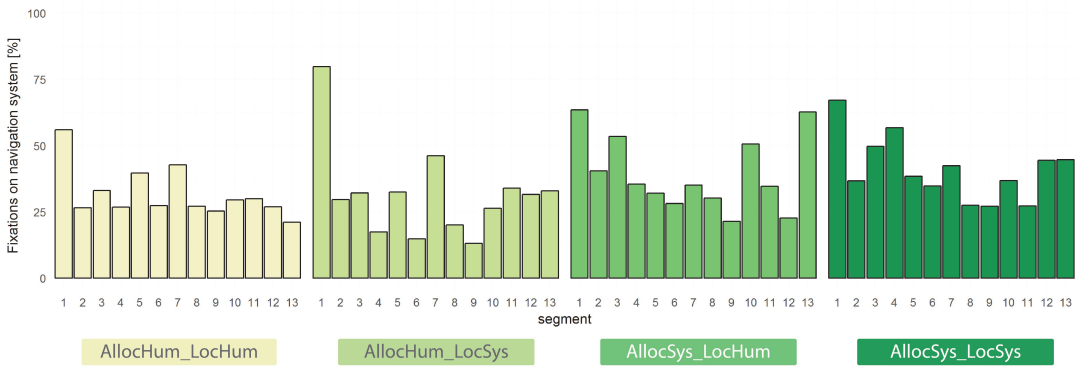

Figure 4.23: Fixation percentages on the navigation system during Phase 1 across the four groups. The highest percentages are in the first segment of the route.

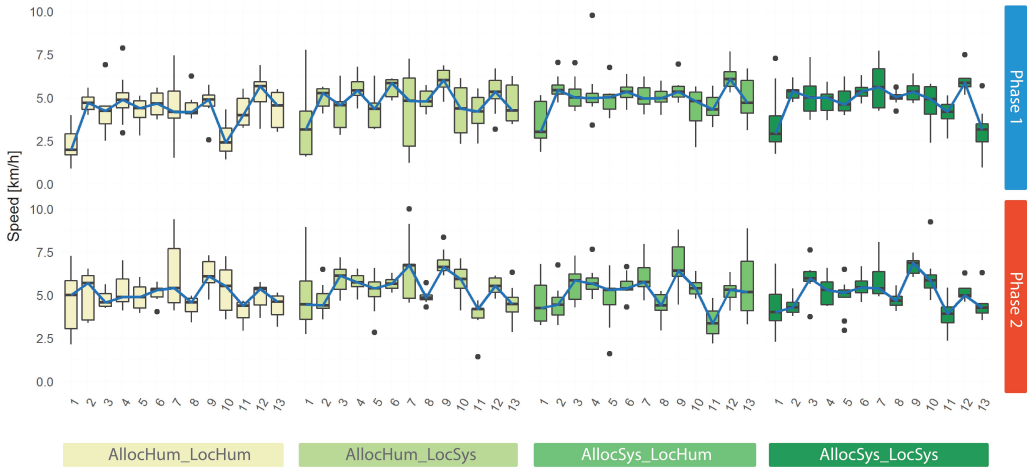

Figure 4.24: Changes in walking speed across route segments, experimental phases, and groups.

Table 4.1 summarizes the main findings from Experiment 1.

Measured variable	**Main Findings**
Navigation Efficiency	The navigation system design does not influence navigation efficiency. It is possible to involve users more (with less assistance) in the navigation process without harming navigation efficiency.
Stops and Hesitations	Less assistance leads to slightly more stops and hesitations during Phase 1 because humans have to deal with the information from the environment.
Markers	Self-chosen markers (AllocHum_) were placed at similar locations along the route as the automatic notifications (AllocSys_). Visible clusters of markers were placed around turns, highlighting the importance of personalized landmarks at intersections.
Map Interactions and Behavior types	There are significant differences in map interactions (e.g., changing the scale of the map) between the navigation system groups. Many participants used all of the interactive tools several times. Participants in the AllocSys_LocHum group (with the worst spatial knowledge) constantly used the interaction tools, resulting in a regular pattern along the whole route and could indicate distraction from attention to the environment.
Navigation Errors	Navigation systems with more assistance led to more navigation errors during Phase 2. Participants did not acquired enough spatial knowledge during Phase 1 when using these systems. In general, most participants did not make any navigation errors.
Gaze Behavior	The spatial segmentation method allows us to analyze the mobile eye-tracking data collected in a dynamic outdoor environment. The results showed distinct behavior differences between navigation tasks (e.g., assisted and unassisted) rather than between navigation system designs.

Table 4.1: Experiment 1: Summary of results

4.4 Discussion

I applied the proposed WALK-AND-LEARN framework in Experiment 1 to assess pedestrians' navigation behavior during an assisted and unassisted navigation phase within a real-world urban environment. The navigation behavior of participants during the assisted phase is analyzed as an indication of the performance during the unassisted phase. I specifically focused on four navigation system designs that provided more or less assistance for the navigator to self-localize and to allocate attention to relevant environmental features. I hypothesized that the higher the assistance from the system, the better the navigation performance, and the lower the incidentally acquired spatial knowledge. Furthermore, I hypothesized that differently automated navigation systems interact with cognitive processing. This, in turn, can affects map interactions and gaze behavior.

4.4.1 Navigation performance during assisted navigation

The results do not support the hypothesis that navigation systems with more assistance lead to better navigation performance. All participants, independently of the used navigation system, needed the same amount of time to reach the destination and followed the route without making any navigation errors. Prior studies typically compared navigation performance between different types of navigation assistance, e.g., digital navigation systems and analog maps, and found distinct advantages for navigation systems over analog maps on navigation performance (Dickmann, 2012; W.-C. Lee & Cheng, 2008; Münzer et al., 2006). I have demonstrated that navigation systems that provide less automated assistance and thus demand more human decision-making do not result in more time needed to follow a given route from start to finish. Human-centered navigation system designs invite the person to proactively attend to the environment and to be in control of this process, as stated by Kiefer, Giannopoulos, Anagnostopoulos, et al. (2017) and Kraft and Hurtienne (2017). Although participants stopped more often with the added effort of allocating their attention toward self-selected landmarks (by pressing a button and by typing the name or description) than participants whose system decided where and to which landmark to allocate their attention to, they were equally efficient

in reaching their destination. Participants with less assistance walked alternately fast and slow along the route, while participants with automatic notifications walked at a constant speed. The dynamic walking behavior can be seen in the walking speed result derived from the eye-tracking data. Overall, these findings of the navigation performances are unique because they successfully demonstrate how automated navigation systems can be designed with cognitive processes that are typically needed during analog map use. Importantly, all four navigation system designs fulfill the overall goal to guide humans efficiently and successfully through a city (Allen, 1999; Slocum et al., 2009). However, we do need to determine how they support humans in finding their way back without assistance.

4.4.2 Notifications interrupt spatial knowledge acquisition

The results for the cognitive process of "allocation of attention" support the hypothesis that navigation systems that give more assistance for the navigator lead to less incidentally acquired spatial knowledge. The different navigation system designs implemented the allocation of attention with two modes at the extreme ends of the spectrum of automatic navigation assistance. The results confirm the association between extreme modes for acquiring knowledge. Both groups that allowed the participants to determine where to add landmarks to the system, thereby knowing where to allocate attention showed an 82% success rate in finding the exact same route back. In contrast, two study groups with notification texts that popped up when approaching the landmark showed success rates of 63% and 38%. It may seem surprising that after walking just ten minutes along a route, many participants in the two notification groups did not find their way back without making a navigation error. However, it is not surprising when looking at the findings of U. Lee et al. (2014) and Pielot and Rello (2017), who demonstrated that system notifications can interrupt an activity. Participants were distracted in their process of information collection, which led to decreased situational awareness (Guinote, 2017; Parasuraman, 2000; Zacks & Tversky, 2001). The adaptive automation with a pop-up marker and text notifications forced participants to switch to the survey perspective at the system's discretion, while participants in the other groups could maintain their

first-person perspective until deciding for themselves to make the switch to the survey perspective on the map, in order to make a place-action link (Chrastil & Warren, 2012). Navigation decisions were taken away from participants by the system with automatic notifications, and thus may have interrupted their process of acquiring spatial knowledge. The result is in agreement with the hypotheses formulated by Chrastil and Warren (2012), Parush et al. (2007), and Willis et al. (2009) that activating a user with a location-dependent task, in this case typing three self-selected landmarks with keywords into a navigation system, helps to selectively and mentally process spatial information and also increases spatial knowledge acquisition.

The results of the eye-tracking analysis revealed that participants who received notifications from the system also spent more time looking at the navigation system within the street segments that contained the notifications, compared with adjacent street segments without notifications. Textual notifications of landmarks, indicated by tactile alarms and defined by the system at specific locations, forced the users to focus on their navigation system rather than on the environment. This was only possible to find with the segmentation method, as it allows the users to differentiate the gaze behavior between spatial locations along the route. The spatial segmentation method reveals where notifications from a navigation system force the navigators' attention on to the navigation system along the route. The percentages of fixations toward the navigation system in segments represent a clear advantage over a total percentage of fixations toward the navigation system for the whole route, as reported in a study with motorists by Haupt et al. (2015), for example. Contextual differences due to the environment can be uncovered with this method. The eye-tracking results support the divided attention literature (Gardony et al., 2013) and align with the stated cognitive problem of the "passive nature of interaction" of navigators when using navigation systems (Willis et al., 2009). The question now is whether people who interact more with a navigation system to determine their current location might be able to increase their success in finding the same route back, compared to people who do not interact as much with the system.

4.4.3 Map interactions both support and hinder spatial knowledge acquisition

The results of the cognitive process of "self-localization" do not support the hypothesis that navigation systems with more assistance for the navigator lead to less spatial knowledge acquisition. A possible explanation for insufficient spatial knowledge acquisition may lie in the interaction behavior of the navigator with the digital map. The participants had two options to determine their current location. First, they could match the environmental information with the map. For this, they continuously used interactive map tools (Meilinger et al., 2012). The WALK-AND-LEARN framework allowed the participants to change the map scale and to rotate, pan, and tilt the map, thereby adjusting the map display according to their individual needs without any restrictions. Second, the participants could use the GPS signal that updated their current location on the map (Kaulich et al., 2017; Rinner et al., 2005; Schwinger et al., 2002). With the GPS signal, the navigation system automatically performs self-localization instead of the navigator, who needs to do this with analog maps (Meilinger et al., 2012; Thorndyke & Hayes-Roth, 1982). I implemented the traditional blue dot for self-localization in two ways. The system-centered way allowed participants from two groups to confirm their current location with the permanently available blue dot on the map. The more human-centered way allowed two of the groups to press a button to get their position displayed on the map when needed. If participants with the button were interested in knowing their current location, they could either press the button to get the blue dot displayed or they could adapt the map in order to facilitate the matching of map and environment. Interestingly, the groups used the two interaction types for self-localization in very different ways, resulting in differences in spatial knowledge acquisition.

Participants interacted more with the digital map (e.g., by zooming in the map) when needing to press a button for self-localization, compared to participants who had the blue dot permanently available. However, participants who interacted more with the digital map performed neither worse nor better than the more passive participants. It is possible that the group with the permanently available blue dot engaged with the interactive map tools in a more strategic and goal-directed manner to get assistance from the navigation system

than the participants with the GPS button. This finding shows that the simple total number of map interactions is neither an argument for inefficient navigation performance nor an indicator for insufficient spatial knowledge acquisition. The number of map interactions depends on additional tasks that the participants were doing during the assisted route-following task.

Participants who interacted more with the map but hardly pressed the GPS button to display their current location acquired enough spatial knowledge to find their way back. In contrast, participants who also interacted more with the map tools and often pressed the GPS button did not acquire enough spatial knowledge to find their way back. The group with the worst performance in finding their way back not only interacted a great deal with the map but also constantly pressed the GPS button to display the blue dot. They may indeed have needed repeated confirmations of their current location on the map to successfully find their route but at the same time, they may also have got distracted by the interactive map elements. It is also possible that they had to offload cognition to the system in order to reduce "stressful" cognitive activity, which would confirm the findings of O'Mara (2019) and Willis et al. (2009). Interestingly, the participants made different decisions regarding pressing the button based on another cognitive process (i.e. allocation of attention) implemented in the system.

The group who additionally needed to choose and type keywords about landmarks had this particular task to concentrate on. They hardly used the self-localization button but did interact a lot with the map to facilitate the matching of map and environment, and simultaneously acquired sufficient spatial knowledge to successfully find their way back. In contrast, the participants of the worst-performing group, who did not have an additional task to fulfill, used the button much more often and consequently had their position displayed on the map for a longer amount of time, while still extensively interacting with the other map tools. Therefore, the experiment confirmed that the so-called action automation in systems, which is an automatically executed process after a person presses a button (Parasuraman et al., 2000), can lead to intended and unintended usage of interactive elements (Janlert & Stolterman, 2017b). Either the system users barely use a button, or they cannot resist such an interactive component of the interface and constantly use a button (Kool et al., 2010). Just having the option of pressing a button likely distracted the participants in the

worst-performing group more than was expected. The result of button presses seems consistent with research that found that increased use of smart devices can lead to excessive reliance on them (Klippel et al., 2010; Parush et al., 2007). Navigation system use may diminish humans' navigation skills more generally, meaning that they may not be able to appropriately judge when the use of a navigation interface element becomes optional (Janlert & Stolterman, 2017b; Montello, 2009).

Another finding is that the participants across the groups either zoomed or changed the map to a smaller scale to better identify the exact location of their destination. They also did this at different locations along the route. The findings related to zoom behavior suggest that specific locations (e.g., at turns after intersections) demand a more detailed allocentric view to match the information from the map to the information in the environment for orientation purposes (Dai et al., 2018; Gardony et al., 2013). This process results in dividing humans' attention between the survey perspective provided from the navigation system (i.e., the allocentric view) and the route perspective from the first-person view of the surrounding environment (Gardony et al., 2013; Ishikawa et al., 2008). Frequent changes in perspective can interrupt the allocation of attention resources to the surrounding environment and can result in fragmentation of attention along the route (Willis et al., 2009). Consequently, the worst-performing group seemed to have paid more attention to the navigation system than to the environment, compared with the other groups. In order to better understand navigators' perspectives during assisted and unassisted navigation, I analyzed gaze behavior from mobile eye-tracking data in more detail.

4.4.4 Navigation assistance and task influence gaze behavior

The results of the gaze analysis reveal that humans spend approximately one-third of their attention on the navigation system and two-thirds on the walking direction, independently of the navigation system design. The overall gazes in the forward direction increased when participants were not using a navigation system (Phase 2 of the experiment) compared to when they were. Fixations to the right and left

of the participants in their walking direction were surprisingly low during both phases. The results could not confirm what Haupt et al. (2015) found: that more and longer fixations to either side (left and right) for a motorist indicated the search for features relevant to navigation and orientation. One explanation might be that car drivers have a greater field of view on either side compared to pedestrians, who have a restricted field of view when walking alongside linear features (e.g., walls of buildings). Another explanation might be the speed difference between motorists and pedestrians. Pedestrians have more time to attend to what is ahead of them for wayfinding decisions without needing to look to the left or right to orient themselves. The annotation process of the recorded eye data to areas of interest is laborious due to individual walking speeds and viewing directions in a constantly changing spatio-temporal context (Kiefer, Giannopoulos, Anagnostopoulos, et al., 2017). Therefore, the method of spatial segmentation provides an alternative to analyzing the whole dataset more quickly across participants, groups, and spatial contexts.

The results of the spatial segmentation did not reveal any differences in the participants' gaze behaviors across navigation system designs, but, interestingly, it did show differences between the two experimental phases. A clear gaze behavior pattern emerged during the assisted route-following task. The pattern is like a wave starting with segments of longer fixation durations, followed by segments of shorter fixation durations, and followed again with longer fixation durations toward the end of the route. No clear patterns emerged during the unassisted route-reversing task. With the segmentation method, I was able to detect route segments that led to higher mean fixation durations, thus potentially indicating higher levels of cognitive processing (Duchowski, 2017). The results could not confirm a direct relationship between mean fixation durations, the percentage of fixations on the navigation systems, and the interactions with the map. However, they do confirm that the use of navigation systems influences the attention paid to the surrounding environment (Gardony et al., 2013; Parasuraman, 2000; Willis et al., 2009) and highlights the significant impact of smart devices and the environment on navigators' gaze behavior.

4.4.5 Summary

The first experiment suggests that differences in navigation system design - specifically related to self-localization and the allocation of attention - affect human navigation behavior and incidental spatial knowledge acquisition. I can confirm that the findings from a prior lab experiment by Parush et al. (2007) also apply in a real-world navigation experiment. My results also imply that the use of interactive map display elements (e.g., zoom, pan, rotation, GPS button, etc.) invites navigators to change the map display and thus modulates the division of navigators' attention between the navigation system and the traversed environment. Participants needed to access information from the navigation system and to interact with the system in order to successfully perform the route-following task. These findings highlight the importance of attempting to better understand the effects of interactive interface components in navigation system designs because they can support, as well as hinder, spatial knowledge acquisition, even if they may not affect navigation performance. I applied the proposed WALK-AND-LEARN framework to the first experiment and started to build knowledge on pedestrian behavior when using navigation systems during real-world navigation, as suggested by Dai et al. (2018). The findings from Experiment 1 led to the design of Experiment 2.

Chapter 5

EXPERIMENT 2

Experiment 1 showed that the participants' behavior varied with different levels of automation of the cognitive processes of "self-localization" and "allocation of attention". In particular, "self-localization" led to a diverse range of behaviors regarding map use and spatial knowledge acquisition that are dependent on different levels of automation in navigation system designs.

As the automatic display of "self-localization" information is one of the key advantages of using mobile digital maps, I further analyzed this cognitive process in a second experiment. In order to better understand the process of self-localization information provided by the navigation system, I changed the spatial (and thus also the temporal) availability of the two different levels of automation. I then analyzed the consequent human navigation behavior as well as spatial knowledge acquisition.

5.1 Research question and hypothesis

In Experiment 1, participants had the self-localization information permanently available, either in form of a blue dot or as a button to display the current location. The question I wanted to answer was whether restricted access to the automated self-localization information would change navigation behavior and spatial knowledge acquisition. Therefore, I identified the following research question for the second experiment.

How do varying navigation system designs with spatially restricted access to levels of automation for "self-localization" influence navigation performance, spatial knowledge acquisition, map interactions, and gaze behavior during navigation tasks in a real-world, urban environment?

I hypothesize that the participants' navigation performance will be worse when self-localization information is restricted compared to non-restricted information, independent of the levels of automation. As the self-localization information from the system will be available in restricted areas, participants need to update their location by themselves between these areas. This is time-consuming but should make participants confident in having the ability to self-localize without the system. Furthermore, participants know that the system allows them access to self-localization information at intersections, but they may feel uncertain of where exactly they can get access to the information. This may lead them to perform the process by themselves anyway. However, participants might increase their interactions with the map and the environment in areas where no assistance from the system on self-localization is available. This might either reduce their allocation of attention to the environment because they are distracted by the navigation system from perceiving the environment, or it may enhance it because they match the information between the navigation system and the environment. Additionally, I hypothesize that participants will perceive the workload as high and will evaluate the usability of such a design as negative when using a navigation system design with spatially restricted access to information. Overall, the spatial restriction should increase human attention allocation to the environment and improve spatial knowledge acquisition by matching the information from the map to the environment in order to update their position.

5.2 Methods

5.2.1 Participants

A total of 43 participants, mostly students at the University of Zurich and ETH Zurich, who came from a variety of different disciplinary backgrounds, took part in the experiment. None of the participants had taken part in Experiment 1. From this sample, 27 participants were female (63%) and 16 were male (37%). The mean age of the participants was 25 years, ranging from 18 to 43 years (M=25 years, SD=5 years). Again, the experiment was conducted in German. All participants owned a smartphone, thus representing a sample with background knowledge in using mobile digital devices. Before taking part, each participant signed a consent form approved by the Department of Geography at the University of Zurich and were told that they could withdraw from the experiment at any time.

5.2.2 Materials

Study area and route characteristics

The study area was located in an urban neighborhood in the Sihlfeld district close to a trendy nightlife area in Zurich, which was unknown to the participants. The characteristics of the route are displayed in Figure 5.1. The route is approximately 900m long, consists of 12 intersections, and features different kinds of landmarks, buildings, etc. representing a typical European urban environment. The chosen route structure was similar to the route used in a study by Gramann, Hoepner, and Karrer-Gauss (2017). Figure 5.1 (left) shows a Google Maps[1] excerpt with the route highlighted in black. The blue pin at the bottom of the map indicates the starting point, and the black flag at the top of the map depicts the destination. All intersections are annotated with "I-" along with a number indicating their position along the route. The intersection annotations did not appear on the map display for the participants and are only added to this figure to allow references to the intersections within this thesis. The route consists of three right (I-1, I-4, I-9) and four left (I-2, I-6, I-10, I-12) turns in the walking direction from the start to the destination. The turns divide the route into eight straight segments of different

[1] ©2019 Google

lengths. To get an impression of the environment, snapshots for both empirical phases are shown in Figure 5.1.

Figure 5.1: The route consists of 12 intersections (white circles) of which 7 are turns. Snapshots are taken at locations along the route (colored circles) in the walking direction (cones indicate viewing directions from those locations) for Phase 1 (blue) and Phase 2 (red).

Stimuli: Map applications

I applied a between-subject design by varying the levels of automation of one cognitive process (self-localization) during Phase 1 according to the methodology introduced in Chapter 3. The two implemented modes are the same as in Experiment 1 (see Figure 4.3): either the system performs the process on its own (the location of the navigator is updated on the map as a blue dot) or the system provides the navigator with the opportunity to perform an action (e.g., pressing the "GPS on" button) to display the current location on the map for ten seconds, after which the blue dot disappears. Figure 5.2 shows the two levels of automation for the cognitive process of "self-localization" in turquoise (Levels 8 and 10).

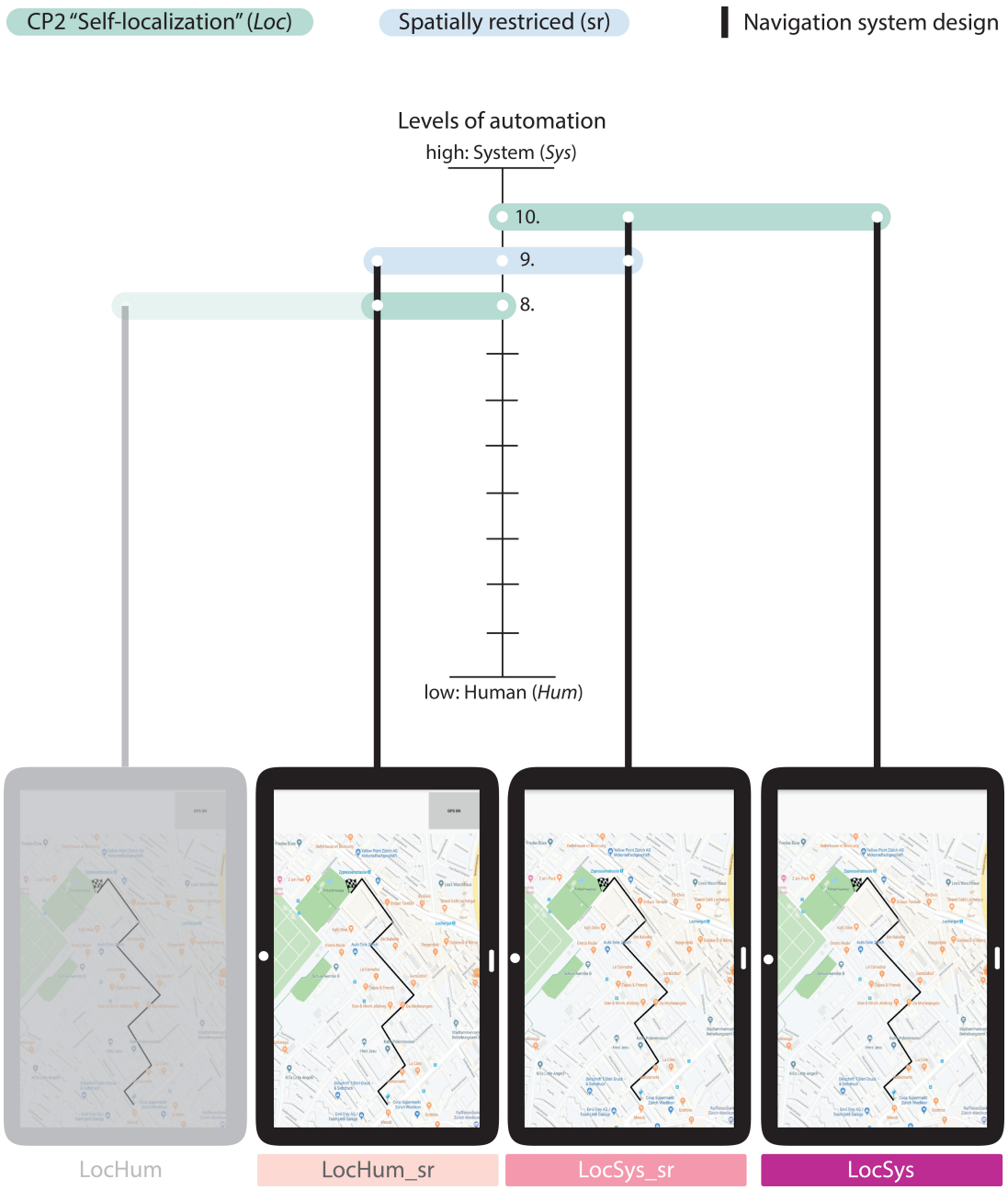

Figure 5.2: Navigation system designs with varying levels of automation of the cognitive process of "self-localization" (Level 8 and 10), and of the systems' decisions to give access only at specific locations (Level 9: spatial restriction). Designs varied from little (left) to highly (right) automated cognitive processes performed by the system.

If the self-localization information is visible on the map without an action from the human, the system uses the abbreviation "LocSys". If the self-localization information becomes visible on the map due to an action from the person, such as pressing a "GPS on" button, the system uses the abbreviation "LocHum", similar to Experiment 1. For the spatial restriction of self-localization information, I implemented the "geofencing" method. Geofencing is defined as the process of tracking a user's location, with the system displaying relevant information when entering a particular area (Rodriguez Garzon & Deva, 2014; Wawrzyniak & Hyla, 2016). Figure 5.3 shows the route in black, with polygons along the route marked in blue. The positions of these polygons are around the intersections. However, due to the shifted GPS signal in some of the narrower streets, the polygons had to be enlarged in order to activate the "geofenced" self-localization information. Participants were only given access to self-localization information from these polygons. This restriction corresponds to Level 9 "The system informs the human only if it the system decides to do so." in the system suggested by Parasuraman et al. (2000). Therefore, participants could use either the blue dot or the "GPS on" button to get the current position from the system when being "inside" these polygons. For the final navigation system design, either the system allows the user to permanently access the information (Figure 5.2 far right and far left "blurred") or the system restricts the availability of the information to specific locations along the route (combination with Level 9 in Figure 5.2). The abbreviation for spatial restriction in the names of the navigation systems designs is "_sr". The two resulting system designs with spatial restrictions are called "LocHum_sr" and "LocSys_sr" and are shown in Figure 5.2 in the middle. For this experiment, I randomly assigned 43 participants to one of three different navigation system designs (14 in the LocHum_sr group, 14 in the LocSys_sr group, and 15 in the LocSys group). The navigation system designs are shown in Figure 5.2. I did not include the fourth design into this experiment for three reasons. First, participants in the AllocSys_LocHum group in Experiment 1 constantly used the permanently available "GPS on" button, essentially imitating the LocSys group. This would be unrealistic to implement in future design solutions. Second, Level 10 automation of "self-localization" (a permanently available dot on the map) is more contemporary for future design solutions. Third, the research question

detailed at the beginning of this chapter can also be answered without including a fourth system design. Based on these arguments, I decided to discard the navigation system design "LocHum" in this second experiment, but I added it in the figure to ensure the experimental design is understood. The three navigation system designs consist of the digital device (a Samsung Galaxy Tab S10.2), the same as in Experiment 1, and an updated version of Google Maps[2] as a base map. Again, the participants could rotate, zoom, pan, and tilt the map according to their needs and without any spatial restrictions.

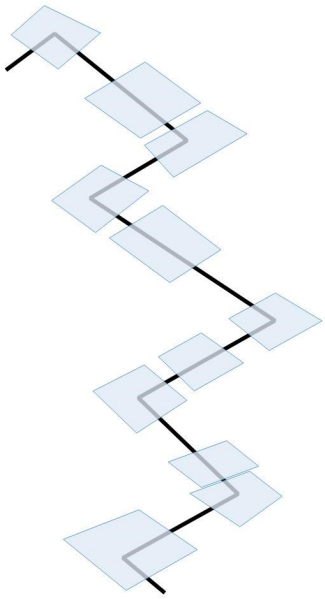

Figure 5.3: Areas (as blue polygons) along the route where self-localization information is automatically activated by the navigation system and is available for the user (either as a blue dot or when pressing the "GPS on" button).

5.2.3 Experimental procedure

The experiment took place during June and July 2019, on days without any rain. The procedure was the same as for Experiment 1 (see Section 4.2.3 for details) except for two additional questionnaires on workload and usability. Figure 5.4 illustrates the procedure for this experiment.

[2] ©2019 Google

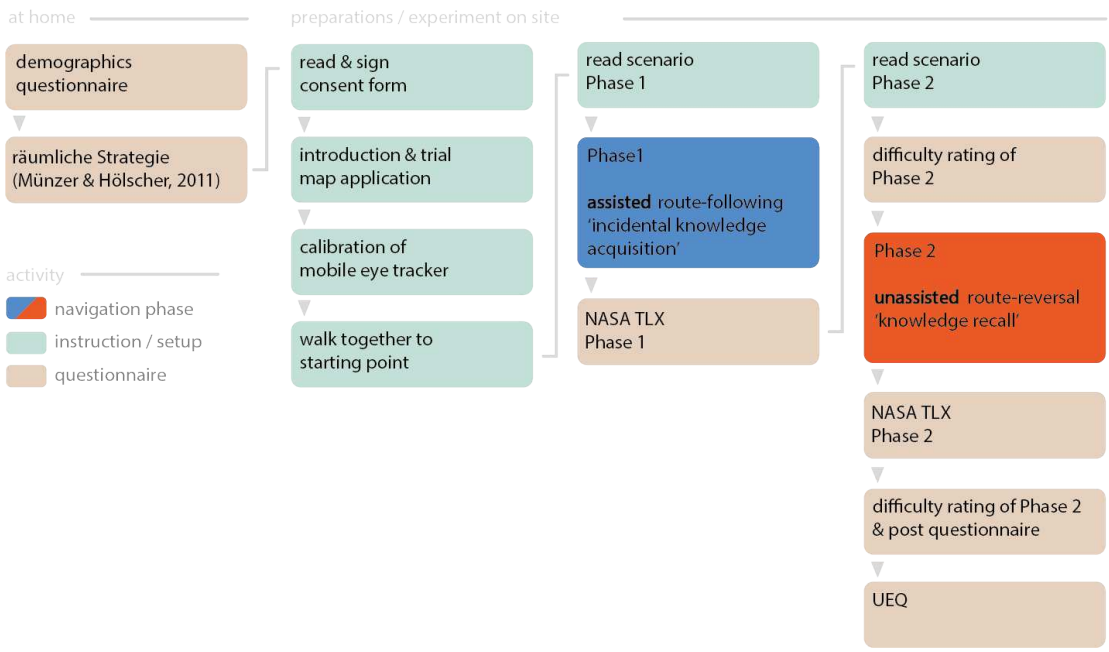

Figure 5.4: Experimental procedure including instructions, setups, and questionnaires. Different from Experiment 1: Task load (NASA TLX) and usability (UEQ) questionnaires. The two navigation phases of the empirical framework are highlighted in blue and red.

After the participants filled out some questionnaires at home (see the demographics questionnaire in Appendix C.1) and arrived at the study site, they were instructed as to the procedure and the navigation system design (each participant was randomly assigned to one of the three applications depicted in Figure 5.2). Additionally, they were equipped with mobile eye-tracking glasses. Guiding them to the starting point, I asked the participants to follow the route provided on the digital map (see the detailed scenarios in Appendix C.3). After arriving at the destination, participants were given the NASA Task Load Index (NASA TLX) questionnaire (on paper, and in German) to get an estimate of the perceived workload for this task (Hart & Staveland, 1988). The assessment consists of six subscales: mental, physical, temporal demand, performance, effort, and frustration, with each being rated from low to high on a scale from 0 to 20.

- Mental demand: The required mental and perceptual activity.
- Physical demand: The required physical activity.

- Temporal demand: The time needed to fulfill the task.
- Performance: Successfully accomplishing the task set by the researcher.
- Effort: The effort needed (mentally and physically) to accomplish a level of performance.
- Frustration level: The feeling of annoyance, discouragement, insecurity, and irritation during the task.

Next, the participants were given the instructions based on the scenario for Phase 2, namely to find the exact same route back to where they "lost" their keys during Phase 1 (see Appendix C.3 for the detailed scenario). The participants were asked to retrace their route and walk unassisted (Phase 2) back to the starting point of the route. After completing Phase 2, the participants were again asked to fill out the NASA TLX questionnaire and rate the difficulty of Phase 2 on a five-point Likert scale. Additionally, the participants were asked to fill out an online post-test questionnaire (Appendix C.2) and to complete the UEQ (Laugwitz, Held, & Schrepp, 2008), which is a standardized questionnaire (the original version is already in German) to determine a user's experience with a product, which includes 26 evaluations categorized into six subscales: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. In this experiment, the products to evaluate were the navigation system designs. The subscales of the questionnaire are briefly explained by the positive endings of the rating scale of the questionnaire:

- Attractiveness: Enjoyable, good, pleasing, attractive, friendly
- Perspicuity: Understandable, easy to learn, easy, clear
- Efficiency: Fast, efficient, practical, organized
- Dependability: Predictable, supportive, secure, meets expectations
- Stimulation: Valuable, exciting, interesting, motivating
- Novelty: Creative, inventive, leading edge, innovative

At the end of the experiment, participants received CHF 20 compensation, signed a confirmation of receipt, and were thanked for taking part. The experiment lasted about 60 minutes, on average.

5.2.4 Data analysis

I have reported the results according to the three groups of the between-subject design. All of the figures follow the same order and are color-coded according to the navigation system design provided in Figure 5.2 (at the bottom). If an analysis involves both experimental phases, they are also highlighted in the corresponding colors (blue and red), as shown in Figure 3.1. All statistical analyses are reported with an appropriate test reported in text and are visualized with boxplots (the black dots represent outliers), bar graphs, or point graphs. A result is statistically significant at a p-value of 0.05. I performed all analyses and visual outputs with R[3] and reported them according to the method suggested by Field et al. (2012). I have either added descriptive statistics (mean and standard deviation) to the text or have referred to the values listed in Appendix C.4. Specifically, the following analysis methods were conducted for the gaze data.

Mobile eye-tracking analysis

Unfortunately, I could only analyze video recordings from 15 of the 43 participants, as they were the only ones who had adequate data quality for both empirical phases. For the other participants, the recordings either stopped along the way due to loose contacts of the cable at the laptop's USB port (technical signs of wear) or because of the laptop overheating (the air temperatures were often around 35°C). This forced me to stop the recordings after completing Phase 1 or after testing several participants in a row. The participants continued to wear the eye-tracking glasses for the whole experiment to ensure consistent conditions of a restricted field of view across all the participants.

The analysis for the eye-tracking data is the same as in Experiment 1, but with a different route segmentation. Again, I segmented the route according to the schematic approach of spatial segmentation introduced in Section 3.4.2. Figure 5.5 illustrates the 13 segments for both empirical phases for the route in Experiment

[3] www.r-project.org (access by 02/07/2020)

2. Given the small sample size, I did not run any statistical analyses on the eye-tracking data.

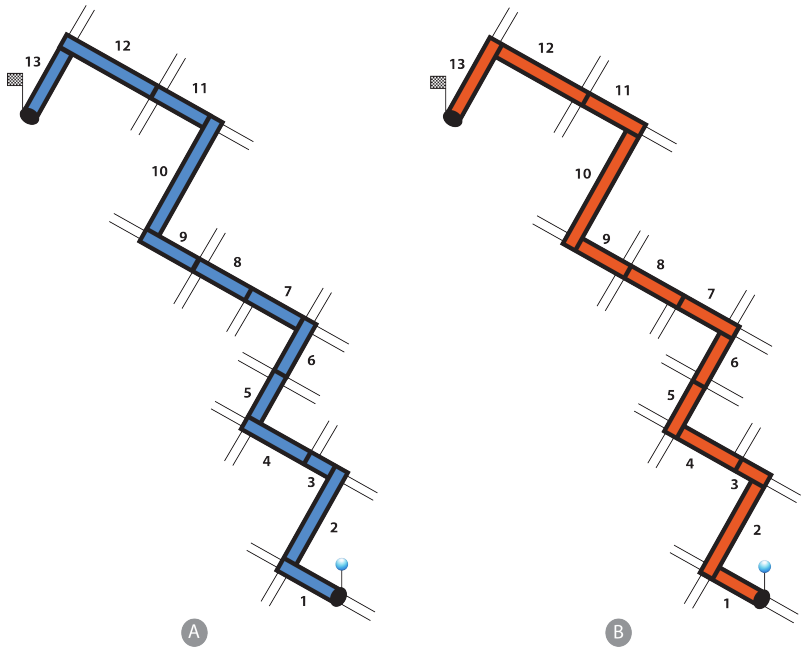

Figure 5.5: Spatial segmentation of the route for Phase 1 (A) and Phase 2 (B).

5.3 Results

The results are based on 41 participants, as I had to exclude two of the participants from the data analysis (one from the LocHum_sr group and one from the LocSys group) who had consistently made a wrong route choice during Phase 1 at intersection I-9 and continued straight on, turned right at the next intersection, and had to turn left at I-11 to get back on the route, which was not the route displayed on the navigation system. If the two participants had learned and remembered the route from the display, they would not be tested on what they had learned before. Therefore, I told the two participants that they had to find the route they just walked back to the starting point and not the route on the navigation system. However, they made navigation errors at exactly the same intersections as during Phase 1. Therefore, I excluded them from the whole data analysis.

5.3.1 Participants

Along with their demographics and self-assessed spatial strategies, I asked the participants to report how often they used any kind of map application on their digital system with a five-point Likert scale in an online questionnaire. All the participants had used a mobile map application at least once every two weeks and were familiar with reading maps in general. The majority (89%) of the participants rated their experience with GIS, cartography, and orienteering as little or none. These results suggest a relatively homogeneous sample of participants in terms of map use in general, and experience in using digital maps, specifically.

The *Räumliche Strategie* questionnaire by Münzer and Hölscher (2011) reveals self-assessed spatial abilities in three different scales. The higher the scores, the more accurately the participants assessed their ability. For the total score, there were no significant differences in ratings between the three groups ($H(2)=0.31543$, $p=0.8541$, with a Kruskal-Wallis test). Furthermore, there were no significant differences in ratings across the groups for any of the scales (egocentric, $F(2,38)=0.609$, $p=0.227$; survey, $F(2,38)=0.74$, $p=0.484$; cardinal, $F(2,38)=2.7251$, $p=0.07835$) tested with a one-way ANOVA. A Kruskal-Wallis test revealed that ratings for Question 12 were also not significantly different between the groups ($H(2)=4.167$, $p=0.1245$). These results indicate a homogeneous distribution of spatial strategies across the three participant groups. The means and standard deviations of the questionnaires' scales across groups and phases are listed in Appendix Table C.1.

5.3.2 Navigation performance

To evaluate the participants' navigation performance, I analyzed the same four standard measures as in Experiment 1: time to task completion (navigation efficiency), number of stops and hesitations along the route, interactions with the map, and navigation errors.

Navigation efficiency

Similar to Experiment 1, this study aimed to keep navigation efficiency high with different levels of automation in navigation systems. Figure 5.6 shows the time

taken for walking the route from the start to the destination for Phase 1, and from the destination to the start for Phase 2. The time to walk the route ranged from 9 to 15 minutes for Phase 1 and 8 to 16 minutes for Phase 2 (Appendix Table C.2). The Kruskal-Wallis tests revealed no significant differences in completion time between the three groups during Phase 1 (H(2)=0.2693, p=0.874) and Phase 2 (H(2)=3.9167, p=0.1411). This result shows that the different system designs did not affect the time it took for participants to complete the route in Phase 1 or the reversed route in Phase 2.

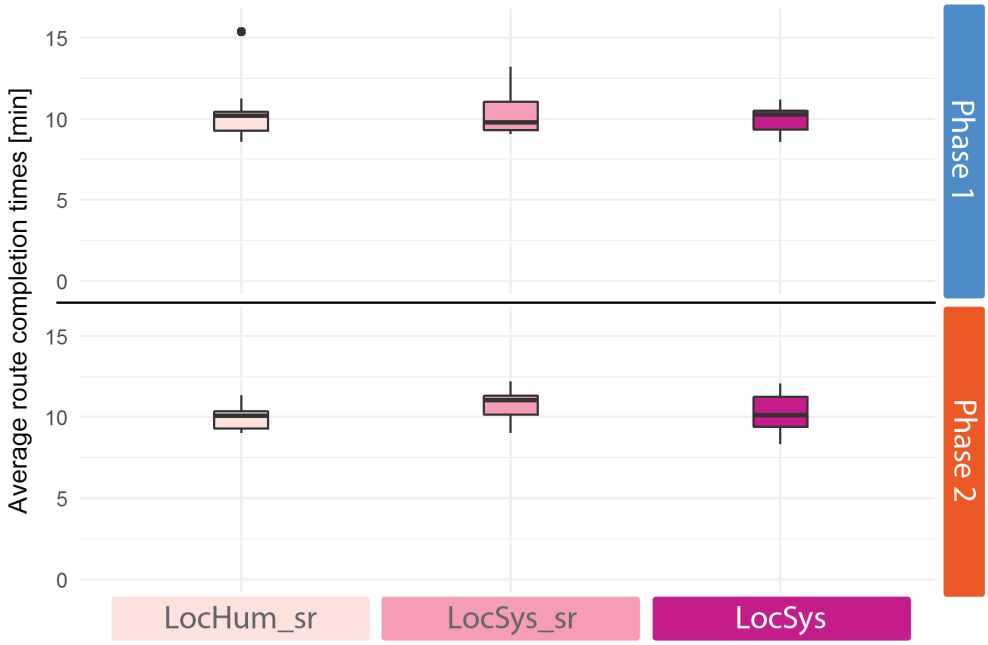

Figure 5.6: A boxplot showing that navigation system designs do not influence route completion times for Phase 1 or Phase 2. Values show the average time taken for walking the route.

Stops and hesitations

Two other indicators for navigation performance are stops and hesitations. Figure 5.7 shows the number of times the participants stopped or hesitated (slowed down) along the route. During Phase 1 and Phase 2, all of the groups barely stopped (Appendix Table C.3). In addition, very few of the participants hesitated during Phase 1, although all the groups hesitated slightly more often during Phase 2.

However, the results showed no statistically significant difference in the number of stops and hesitations between the groups or the phases (p>.05).

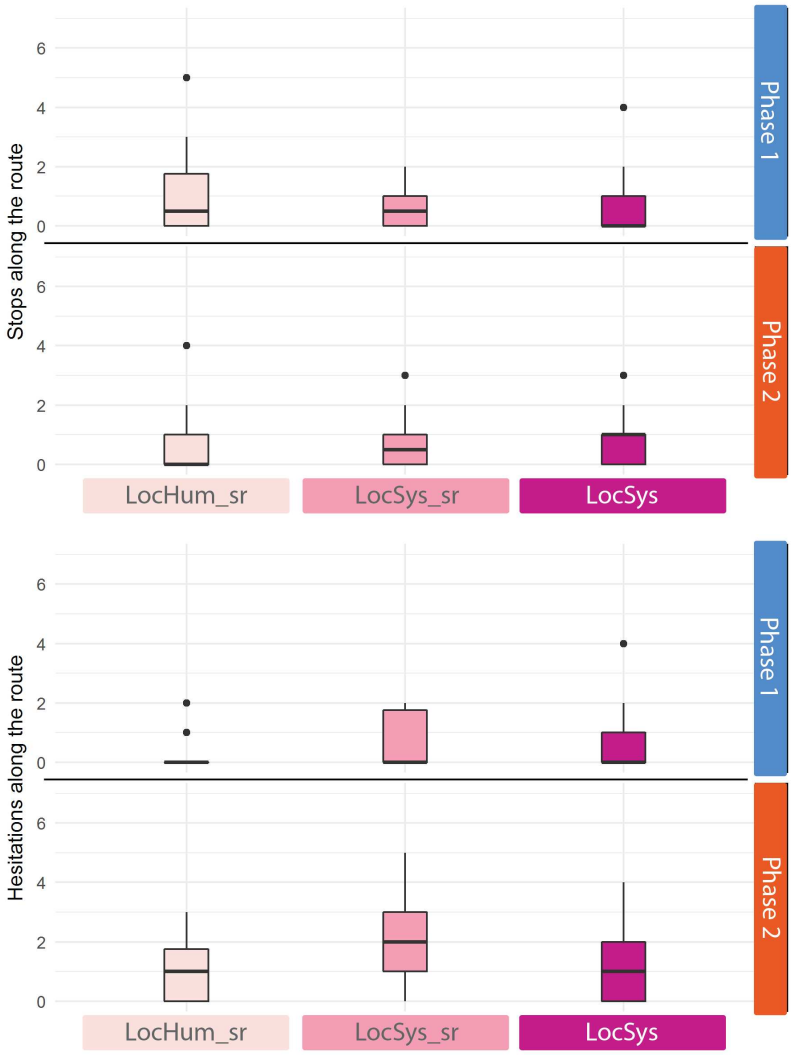

Figure 5.7: Boxplots showing a small number of stops and hesitations across the groups for Phase 1 and 2.

Map interactions

The navigation system recorded the number of times a participant in the LocHum_sr group would press the "GPS on" button as well as all their interactions with the map in a log file. Within the areas of spatial restriction, the

participants in the LocHum_sr group could have displayed their current location on the map by pressing the "GPS on" button, while the two other groups did not have this button available to them. Figure 5.8 shows that participants did not use the button frequently, with most participants only using it once. Therefore, the time in which the self-localization dot on the map was available compared to the whole duration of Phase 1 was very low. This means that most of the time, the self-localization had to be done by the participants themselves, and they hardly ever needed the information from the system (Appendix Table C.4). This is in contrast to the result from Experiment 1, where the button was frequently used by the participants in the AllocSys_LocHum group (see Figure 4.12).

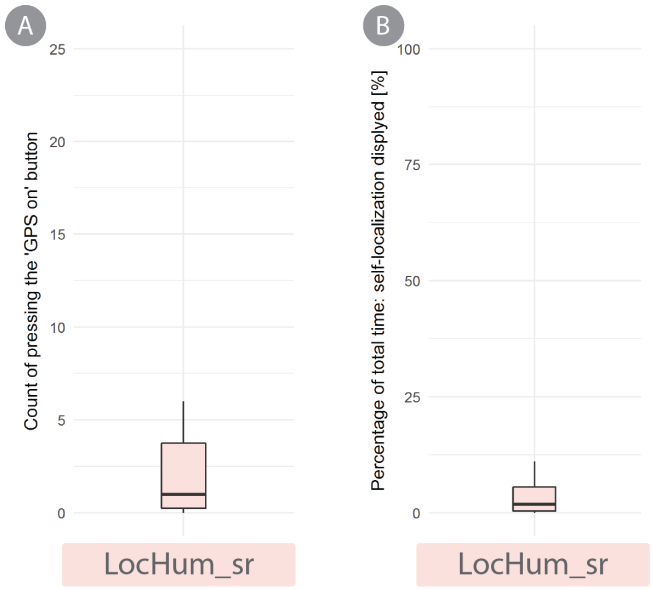

Figure 5.8: "GPS on" button use (A) and duration (as a percentage of the total time of Phase 1) of available self-localization information on the digital map (B).

The navigation system recorded the number of times a participant changed the map (zoom, rotate, pan, tilt the map). Figure 5.9 presents the number of interactions across the three navigation system groups. Similar to the results in Experiment 1, some participants interacted frequently with the map, while others interacted with it much less frequently (Appendix Table C.5). A Kruskal-Wallis test revealed no statistically significant difference in the number of interactions across the three groups (H(2)=1.2977, p=0.5227). Participants with a navigation

system that spatially restricted self-localization information did not interact with it any more or less than the participants who had the information permanently available.

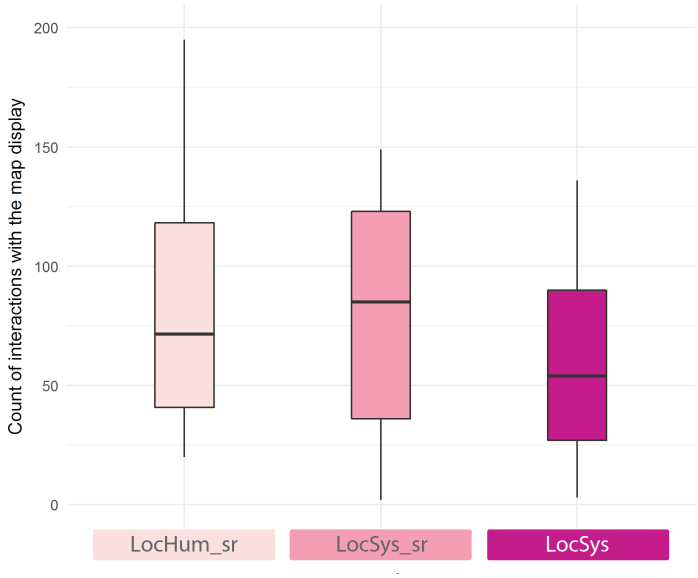

Figure 5.9: The boxplot shows no statistical differences in the number of interactions (zoom, rotate, tilt, pan) with the map display during Phase 1 across the groups.

The spatial distribution of the map details revealed clear spatial patterns for each type of interaction. As in Experiment 1, each point of the Figures (5.10, 5.11, 5.12) represents the center of the map. Figure 5.10 shows the spatial pattern of zoom levels. The higher the zoom level the smaller the map scale (dark blue), and the lower the zoom level the larger the map scale (bright blue). The results show that the larger the map scale, the more central the map center lies when taking the whole route (from start to destination) into account, and the bigger the overview of the whole area around the route. Similar to Experiment 1, the center of the map is closer to the route when participants set the map to a smaller scale indicating the need for more detailed information at their current location. The darker the points (smaller scale), the closer the map centers are located to the route.

Figure 5.10: Map centers are closer to the route with a small map scale and more distant from the route with a large map scale across all three groups. The data are from all 14 or 15 participants per group.

Another interaction with the map is the map rotation, which is usually done to keep the top of the map in the walking direction after (or before) changing direction. The rotation analysis only includes the map rotations of the map rather than the tablet rotation, which was not recorded in a log file. Instead, I gathered the tablet rotations from the video recorded by the eye-tracking glasses for some participants (used for the behavior type figures). Figure 5.11 shows the map rotation activities across the three groups. Again, each point indicates the map center of the activity. The colors indicate the number of degrees in which the top of the map points clockwise from North (which was the starting position). The rotation behavior revealed a clear spatial pattern based on turning points. The route segments pointing at Northeast direction show the rotation category colored in brown (270°-359° or -90°), and the route segments pointing in a northwest direction are purple (0°-90°). The last segment (Segment 13) which has a southwest walking direction (90°-180°) shows a higher density of bright purple points, as the participants had to turn their map accordingly. Furthermore, the map centers are located closer to the route for participants with a navigation system with lower levels of automation (LocHum_sr). For participants with a higher level of automation (e.g., LocSys), the map centers are more distant from the route for map rotations. This could be because the lower the levels of automation, the more the participants had to self-localize by themselves and therefore needed to keep track on the turning points more closely in order to know where they were.

The third interaction with the map is the tilt function. Tilting the map changes the viewing angle on the map and makes the map features appear in perspective - closer features appear larger and more distant features appear smaller. Figure 5.12 shows the changes in the map's viewing angles in degrees across the three groups. The spatial analysis of the participants' tilt activity shows that the tilt function was most frequently used by the LocHum_sr group. Interestingly, the map centers during tilting were closer to the route for the LocSys_sr group than for the other groups. For the LocSys group, the map centers are off the route during tilting, which indicated misuse of the tilt functions. The LocHum_sr group also had the map center placed along the route while using the tilt function of the map during the second half of the route.

Figure 5.11: Spatial pattern of segment direction based on the rotation angle across all three groups. The map centers are closer to the route during lower levels of automation. The data are from all 14 and 15 participants per group.

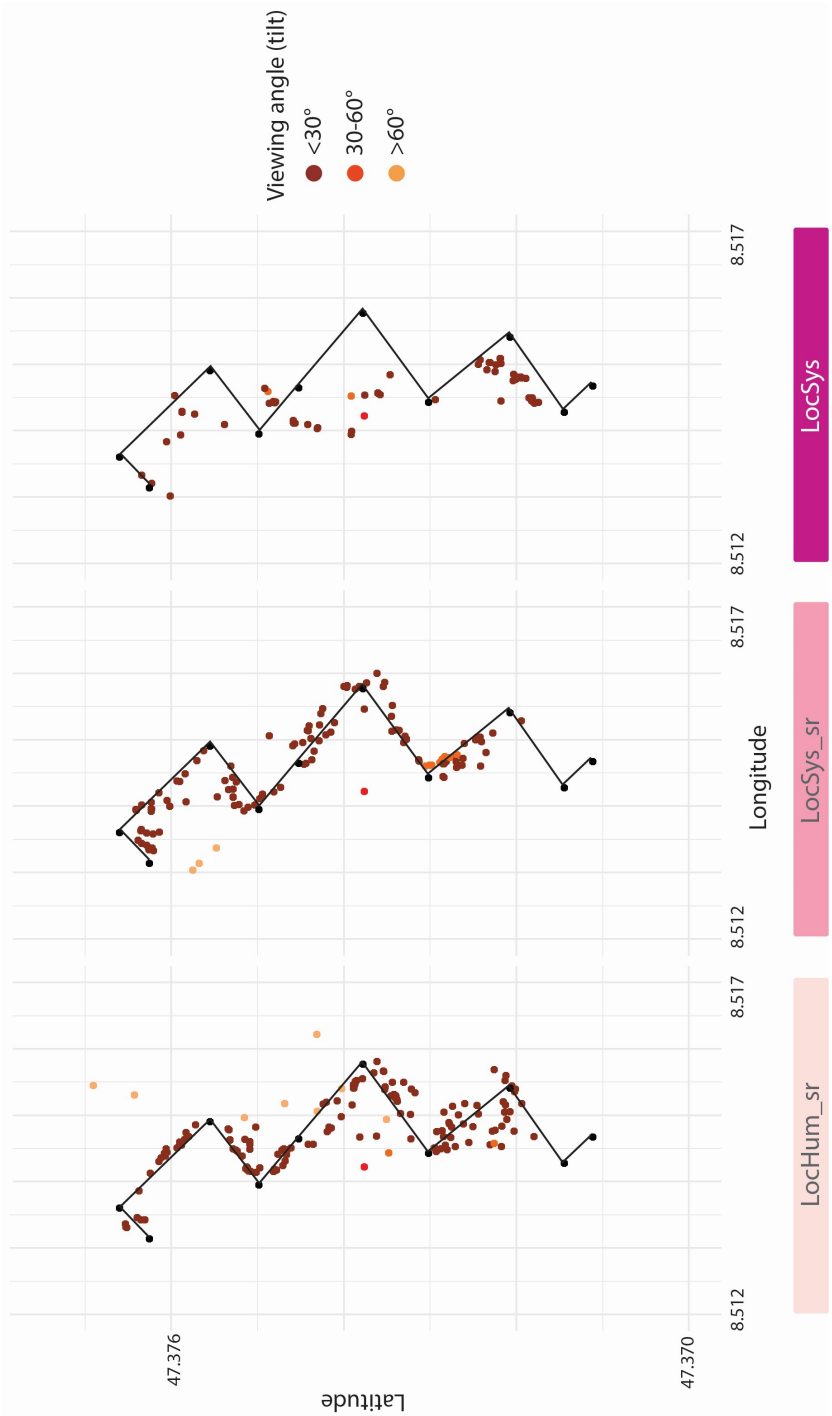

Figure 5.12: The number of tilting decreases and distance of the map center to the route increases with increasing levels of automation. The data are from all 14 and 15 participants per group.

Overall, the spatial analysis of the map interactions reveals that the participants changed the center of the map along the route while performing the route-following task. Panning the map was a task that was applied constantly across all the groups. The activity of panning the map is dependent on the types and levels of map interactions, route directions, and the varying level of automation of the process of "self-localization" (different navigation system groups). What is noticeable is that map centering around turns usually stays in the acute angle of the turn. This is not surprising, as it allows the user to get an overview of the next part of the route and to plan and see ahead with the information available on the map. This behavior is clearly visible in the analysis with the zooming tool (Figure 5.10).

Next, I analyzed the behavior of map interactions among individuals and classified them into the behavior types identified in Experiment 1 (see Figure 4.16). Figure 5.13 shows representative individuals of different behavior types. As seen in the spatial analysis of map interactions, the participants often changed the scale of the map by zooming in or out. This is the dominant type of interaction in all behavior types (Figure 5.13). The constant behavior usually contains the use of the zooming tools (Figure 5.13E). This is in contrast to the result in Experiment 1, where the use of the "GPS on" button mainly defined the constant behavior type, probably due to its restricted availability in Experiment 2. Additionally, rotation behavior can be seen in Figure 5.13B. This participant rotated the map at turnings so as to adjust the map in the walking direction. This behavior also appears in the irresistible behavior type (Figure 5.13D). Participants classified as showing tactical behavior (e.g., Figure 5.13C) needed the assistance from the map at very specifically selected locations along the route without otherwise interacting with the map. The participants shown in Figure 5.13A (zooming behavior) can also be classified in the tactical behavior group. Generally, participants interacted with the map during Phase 1, but the question remains as to how they evaluated the usability of the navigation system design.

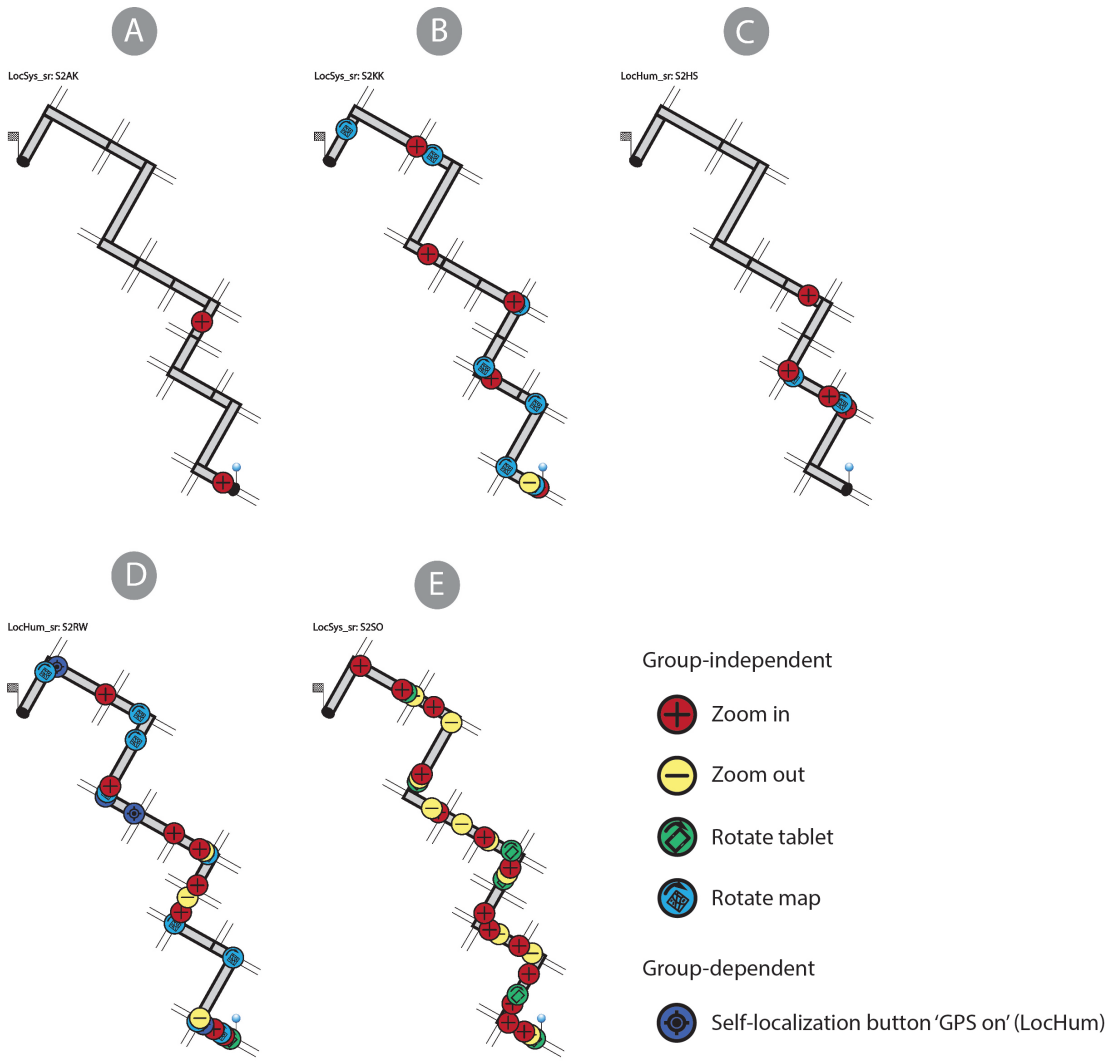

Figure 5.13: Examples of participants' behavior using map interactions: Zooming behavior (A), rotating behavior (B), tactical behavior (C), irresistible behavior (D), and constant behavior (E).

Usability of the navigation system

The usability questionnaire, UEQ, reveals how participants evaluated the different navigation system designs. According to the evaluation method of Laugwitz et al. (2008), the values range between -3.0 (extremely bad) and +3.0 (extremely good), whereas values between -0.8 and 0.8 represent a neutral evaluation, above 0.8 a positive evaluation, and below -0.8 a negative evaluation of the navigation system. Figure 5.14 depicts the evaluation for the questionnaire's six scales (attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty) across the three navigation system designs. The groups do not reveal any differences in evaluation scores within the scales (Kruskal-Wallis test, p>.05) and show positive evaluations in attractiveness, perspicuity, efficiency, dependability, and stimulation. However, participants from all groups evaluated the navigation systems as neutral with regard to novelty. This means that all groups, independent of the implemented levels of automation, evaluated the usability of the system in the same way. Lowering the level of automation did not influence the evaluation of the usability of the system design.

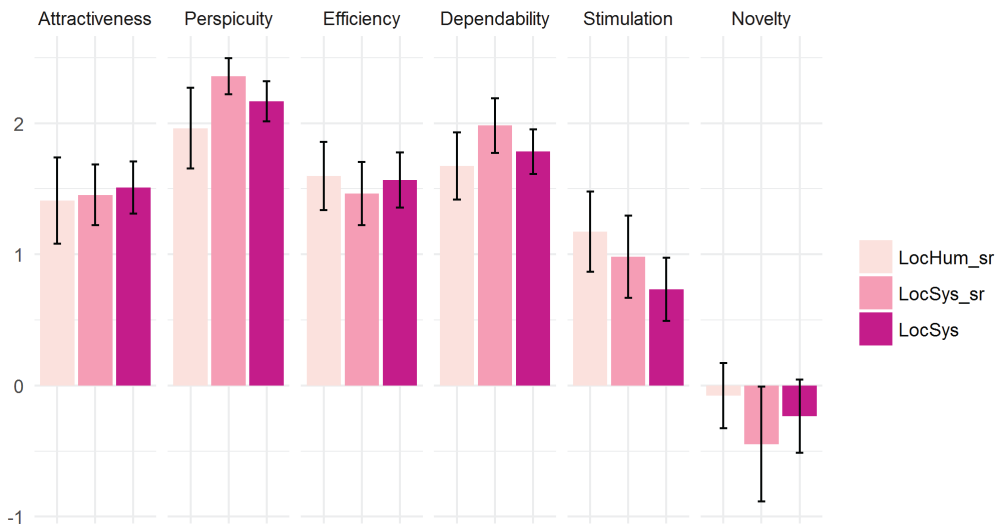

Figure 5.14: This graph shows no statistical differences between the groups within the UEQ scales. There is a positive UX evaluation for five of six UEQ scales across the three navigation system groups. In terms of novelty, all navigation systems were evaluated as neutral. Bars indicate means, including standard errors.

Perceived workload and rating of task difficulty

In order to understand how the participants perceived the workload of the two phases of the WALK-AND-LEARN framework, the participants filled out the NASA TLX questionnaire after each phase. Higher scores indicated a higher workload for the task and vice versa. The scale of performance is inverted, meaning that lower values indicate a good perceived performance while higher values stand for a bad perceived performance. Figure 5.15 reveals the differences in scores between the two phases. The values for perceived workload during Phase 1 are lower than for Phase 2 ($t(245)=-11.061$, $p<.01$). The task load scores of Phase 2 (for all scales) are lowest for the group with the lowest level of automation (LocHum_sr) and highest for the group with the highest level of automation in the navigation system (LocSys) but are not statistically significant ($p>.05$). To better understand the higher perceived workload of Phase 2, I also analyzed the individual ratings of the task difficulty. More specifically, participants rated the difficulty of Phase 2, both before and after performing the task of retracing their route, on a five-Point Likert scale ranging from 1 (very easy) to 5 (very difficult). Overall, participants rated the task's difficulty as neutral (a mean score of 3) with most of the ratings falling between 2 (easy) and 4 (difficult) for all groups, both before and after completing the task (Appendix Table C.6). A Kruskal-Wallis test revealed no significant differences in ratings either before ($H(2)=1.0203$, $p=0.6004$) or after ($H(2)=0.36626$, $p= 0.8327$) performing Phase 2 across the three groups. Although the workload scores increased for Phase 2, the participants (independent of the navigation system design) did not change their rating of the task difficulty after they completed Phase 2.

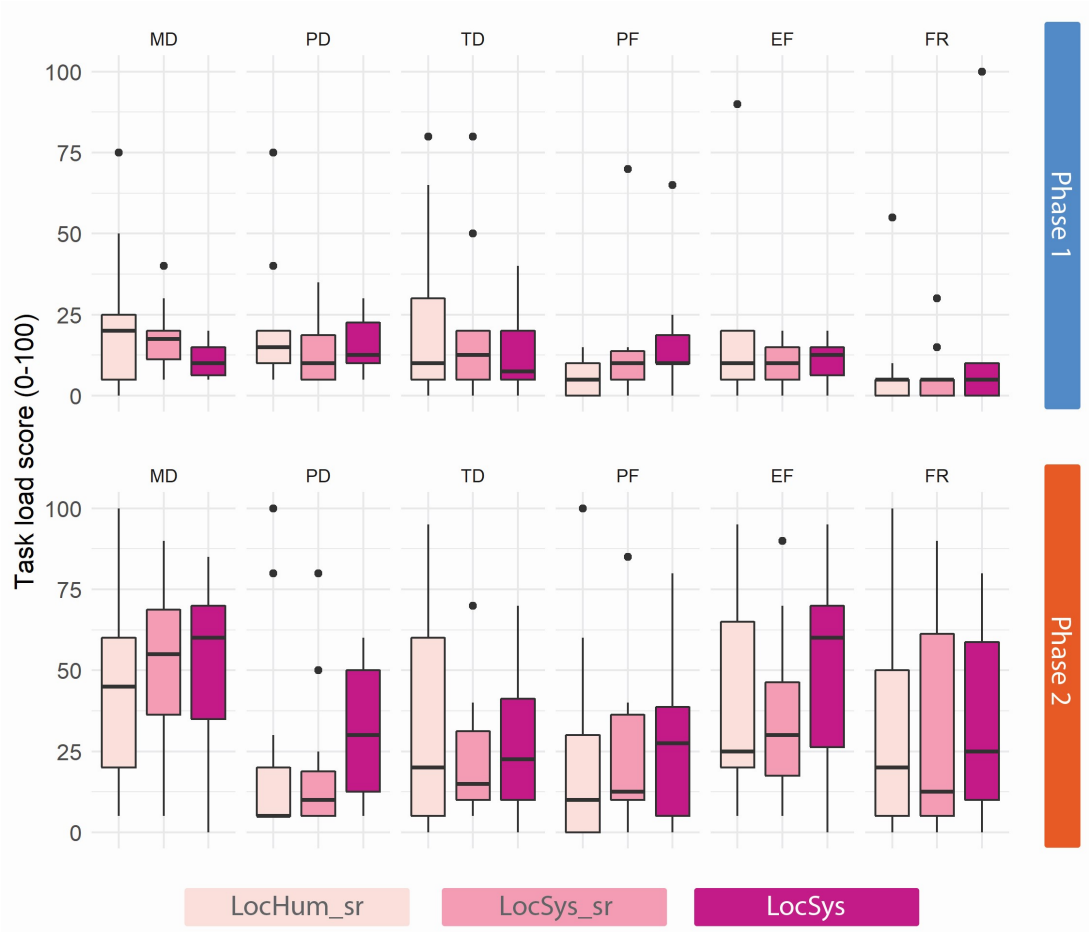

Figure 5.15: NASA TLX scales: Mental demand (MD), physical demand (PD), temporal demand (TD), performance (PF), effort (EF), and frustration (FR) across the groups and experimental phases. High values indicate a high task load, while low values indicate a low task load. For PF, low/high values stand for good/bad perceived performance.

5.3.3 Navigation errors: Indicator of insufficient spatial knowledge

During Phase 2, participants had to find the exact same route back that they had previously followed during Phase 1. Each wrong turn at an intersection was counted as one error. Figure 5.16 summarizes the results for the different groups. In all groups, the majority of the participants made at least one error. In the LocSys_sr group, which was the best-performing group, around half of the participants (8 out of the 14, 57%) made at least one error. In the LocHum_sr group, 8 out of the 13 participants (61%) made at least one navigation error, and 10 out of the 14 participants (71%) made at least one navigation error in the worst-performing group, LocSys. These participants did not acquire sufficient spatial knowledge to reverse the route without making a navigation error. The result indicates that some participants in each group acquired enough spatial knowledge during Phase 1 to retrace the route without navigation errors during Phase 2. The highest number of participants successfully retraced their route using the LocSys_sr navigation system design (Appendix Table C.7). A Kruskal-Wallis test revealed no statistically significant differences in mean error between the groups (H(2)=0.70353, p=0.7034).

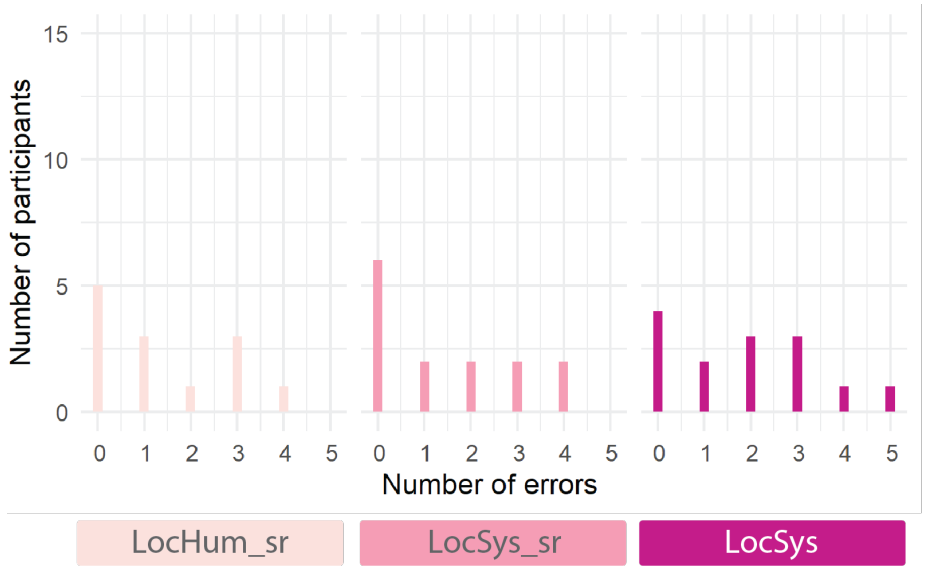

Figure 5.16: Number of participants and the numbers of errors (an indicator for insufficient spatial knowledge acquisition) they made during Phase 2.

5.3.4 Gaze behavior

In this second experiment, I annotated the video data according to the spatial segmentation depicted in Figure 5.5. The eye-tracking device only recorded data from a few participants in the two groups with spatial restrictions. Unfortunately, there is no complete recording for any of the participants from the LocSys group. In total, I annotated 13 participants in Phase 1 (five from the LocHum_sr group, and eight from the LocSys_sr group) and nine participants in Phase 2 (three from the LocHum_sr group, and six from the LocSys_sr group). Figure 5.17 shows the mean fixation durations for each segment during both phases and across the two groups.

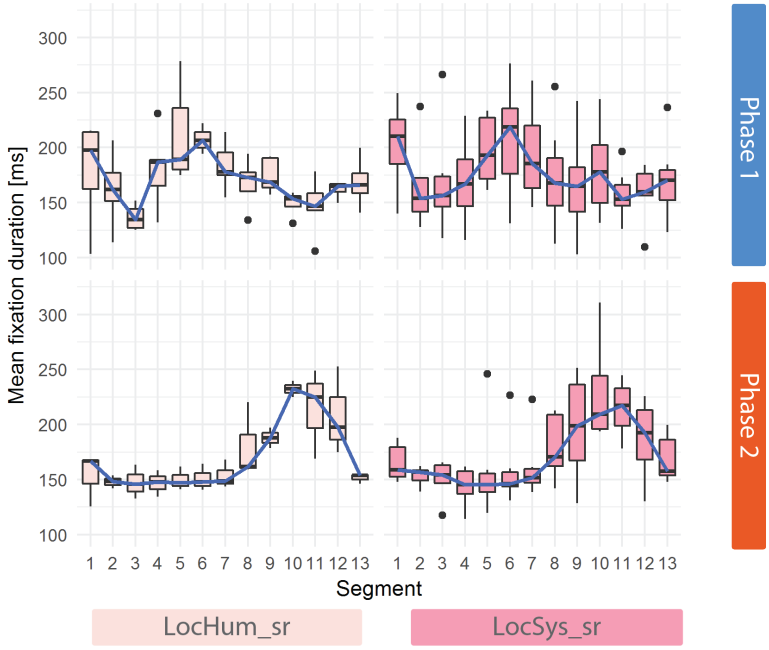

Figure 5.17: Mean fixation duration in each segment of the route across the two groups (with spatially restricted self-localization information from the system) for Phase 1 and Phase 2.

For each participant, the walking direction was from Segment 1 to Segment 13 in Phase 1 (i.e. read the graph from left to right) and from Segment 13 to Segment 1 in Phase 2 (i.e. read the graph from right to left). Similar to Experiment 1, there is a drop in mean fixation durations after the starting point and a rise in

mean fixation durations in the middle of the route. Interestingly, the mean fixation durations for Phase 2 follow the exact same pattern across the two groups. The graph first shows a rise in mean fixation durations, then decreases until Segment 7, before settling on a mean fixation duration of around 150ms for all the remaining segments from 6 to 1. There is a clear difference between the two phases across the segments but not between the two groups. This result confirms the findings of Experiment 1.

A further gaze measurement is the position of the fixations on the screen camera, which records the participants' egocentric field of view. I found that there were distinct patterns within the fixation positions. Figure 5.18 shows that the X coordinate (change in the horizontal direction, right and left) is slightly more dynamic in the LocHum_sr group compared to the LocSys_sr group. In the first segments of Phase 1, participants from the LocHum_sr group tended to look more to their right. In the first segments of Phase 2 (Segments 13-10), they looked more to the left before changing to the right. For the LocSys_sr group, the fixations were mostly in the middle of the screen for the X coordinate for both phases. For the Y coordinate (change in the vertical direction, up and down), participants in the LocHum_sr group focused more on the upper part of the field of view during both phases. Interestingly, the fixation positions in the Y direction of the LocHum_sr group revealed a clear change between Segments 8 and 7. However, the mean fixation position was still in the upper part of the field of view, which could indicate that participants angled their heads toward the ground and looked up with their eyes without moving their head. For the LocSys_sr group, the Y coordinates for both phases revealed no clear pattern. Overall, there is a large range of fixation positions in the horizontal (X coordinate) and vertical (Y coordinate) directions across all the groups, segments, and experimental phases. However, it should be remembered that the analysis of Phase 2 only contained nine participants across the two groups, with each individual contributing significantly to the results. Therefore, the results of the gaze analysis should be interpreted with caution. Again, this result does not explain what the participants were looking at, but the analysis reveals a clear pattern in gaze behavior across the phases and spatial segments.

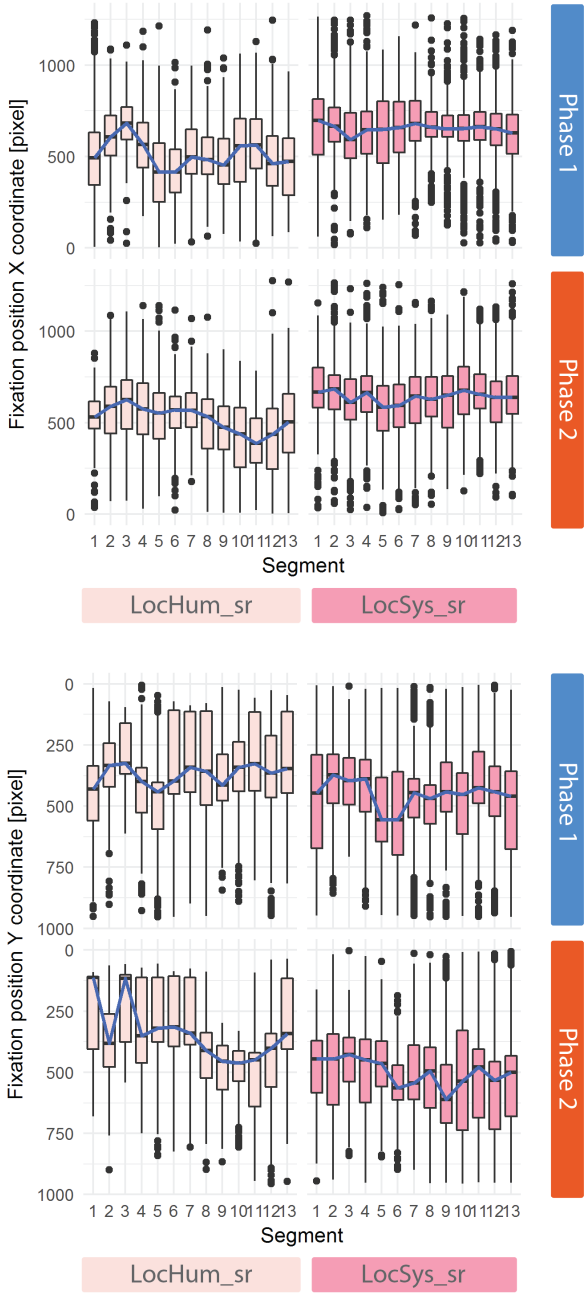

Figure 5.18: Fixation position (X and Y coordinates) of the screen video camera in each segment of the route across the two groups (with spatial restriction) for both phases.

Table 5.1 summarizes the main findings of Experiment 2.

Measured variable	**Main Findings**
Navigation Efficiency	The navigation system design does not influence navigation efficiency in both phases. It is feasible to spatially restrict navigation information without harming navigation efficiency.
Stops and Hesitations	No significant differences were found between the number of stops and hesitations across the groups and phases.
Map Interactions and Behavior Types	There are no significant differences in total map interactions between the navigation system groups. Interactions with the digital map (pan, zoom, rotate, and tilt) reveal distinct spatial behavior patterns during Phase 1. Differences between the groups are small compared to the distinct spatial behavior patterns.
Usability	Overall, there are positive evaluations for the navigation system designs, with the exception of neutral evaluation on the UX scale given to "Novelty".
Task Workload	The perceived workload is low for the assisted navigation phase (Phase 1) but increases for the unassisted navigation phase (Phase 2) for all scales of the NASA TLX across all three groups.
Navigation Errors	In general, a high number of participants make navigation errors during Phase 2. Most participants who did not make an error were in the group with the self-localization information automatically displayed in geofenced areas. These participants acquired enough spatial knowledge during Phase 1 to find their way back without making an error.
Gaze Behavior	Similar to Experiment 1, the results show distinct behavioral differences between navigation tasks (e.g., assisted and unassisted navigation) rather than between navigation system designs.

Table 5.1: Experiment 2: Summary of results

5.4 Discussion

In Experiment 2, I focused on three navigation system designs, of which two restricted automated self-localization information to certain spatial areas along the route. I hypothesized that while spatially restricted access to self-localization information decreases human navigation performance, it increases spatial knowledge acquisition. The main reason for this is that the navigator has to actively update the position between the restricted areas themselves. Furthermore, I hypothesized that different navigation system designs influence map interactions and gaze behavior in a similar way to that seen in Experiment 1.

5.4.1 Navigation performance during assisted navigation

The results did not support the hypothesis that navigation system designs with spatially restricted access to self-localization information decrease human navigation performance. By entering a geographic area at intersections, two system designs would either trigger the display of the blue dot on the map or the button with which the user could display the blue dot on the map. Between these geographic areas, the participants needed to orient themselves by matching the map with the environment, and vice versa. This is a difficult process when using navigation systems, as human cognitive ability is limited (Willis et al., 2009). Surprisingly, spatially restricting self-localization information does not influence the route-following efficiency from the start to the destination. Similar to Experiment 1, the designs tested in Experiment 2 assisted the participants in reaching their goal without making navigation errors. The overall goal of a map is to support the user in efficiently and successfully guiding themselves through space (Allen, 1999; Slocum et al., 2009). The results show that all three navigation system designs fulfill this goal (except for two participants) and support the proposed design solution by Willis et al. (2009) that information should be provided in short segments from the navigation system during assisted navigation.

The results of the usability questionnaire revealed that the users were happy using the systems, regardless of their design. Surprisingly, the participants evaluated the design approach of spatially restricting access to self-localization

information in the navigation system as neutral, although it is unusual for this type of feature to be automated. It is probable that the participants did not consider spatial restriction as being a new, exciting, and unexpected feature. This would make its application in the real world even more acceptable, as it would not change what the users were already used to. Providing a system that efficiently and effectively guides navigators to their destination in a satisfactory manner, which I achieved within this experiment, acknowledges the usability standards (Bevan, 2001) for the design of future navigation systems. However, we need to determine whether the navigation system design also acknowledged the requirements (e.g., by Parush et al., 2007; Willis et al., 2009) of the systems to increase spatial knowledge.

5.4.2 Reasons for insufficient spatial knowledge acquisition

The number of navigation errors made by the participants does not support the hypothesis that navigation systems with spatially restricted access to self-localization information lead to higher levels of spatial knowledge. The number of navigation errors between the groups with the triggered blue dot and triggered button did not differ. Although the success rates of groups with spatially restricted access are still quite low, the results are the first indication that the idea of delivering information in short segments might work to reduce attention on the system, as suggested by Willis et al. (2009). This finding supports literature on attention distraction based on the display of the permanent GPS signal on the map that leads to decreased spatial knowledge acquisition (Ishikawa et al., 2008; Parush et al., 2007). The analysis of the navigation errors revealed two main reasons for the participants' insufficient spatial knowledge acquisition: the map interactions and the complexity of the traversed environment.

Participants across all the groups, with or without spatially restricted self-localization information, frequently interacted with the digital map and did not, therefore, acquire sufficient spatial knowledge to find their way back. A map is usually used for self-localization and orientation within a space (Thorndyke & Hayes-Roth, 1982). When using a map, humans have to match the information from the map - usually from a bird's eye perspective, which is also known as an

allocentric/top-down perspective - to the environment in a first-person perspective, which is also known as an egocentric view (Aretz & Wickens, 1992; Lobben, 2004; Meilinger et al., 2012; Wang, 2017). To facilitate this process, people nowadays are able to zoom in to a smaller map scale to get more details of their immediate environment, to orient the map in their heading direction aligned with the map in the walking direction, or are able to pan the map to maintain the center of the map at the current location. To be able to change the scale of a map is one of the key aspects of mobile maps in navigation systems (Baudisch & Rosenholtz, 2003; Dickmann, 2012; Ishikawa & Takahashi, 2013; Kray et al., 2003; Ware, 2013; Willis et al., 2009). Indeed, the participants often made use of the zooming tool. Although the number of map interactions did not differ between the groups, the types of interactions did reveal distinct spatial behavior patterns between them. The analysis of the zooming behavior reveals that the closer the map center is located to the route, the smaller the map scale. With this finding, I can demonstrate that people use the map tools for their intended purpose, and how context-dependent (e.g., user or environment) the tools are used during a route-following task.

The spatial analysis of the map rotation tool also shows a clear behavior pattern depending on how the streets are oriented in space. For example, participants turned the map clockwise (up to +90° from north) when walking along a northwest-facing street, and anticlockwise (up to -90° from north) when walking along a street facing northeast. This pattern was clear for the group that used the least assistance (LocHum_sr) but was less clear for the group using the most assistance from the navigation system (LocSys). The reason for this could be that the lowest assistance level demanded more actions from the navigator (i.e. pressing a button) in order to get the blue dot displayed. Therefore, the users needed to adjust the map more in order to accurately orient themselves in space. The highest assistance given was when the blue dot was permanently available to the user. The blue dot made the map interactions superfluous because the participant would automatically know their current location on the map. However, the group who had the blue dot permanently available still interacted frequently with the map, and also acquired insufficient spatial knowledge. Besides the need to locate themselves using map interactions, the need to attend to the environment to account for locomotion/safety may have

distracted participants when they could have been acquiring spatial knowledge.

The study area was more complex in Experiment 2 than in Experiment 1 and could be a reason for the insufficient spatial knowledge acquisition. The structure of and locomotion through an environment also influenced spatial knowledge acquisition during navigation (Appleyard, 1970; Carpman & Grant, 2002; Dai et al., 2018; F. Martin & Ertzberger, 2013; O'Mara, 2019). The appearance and structure of the surrounding environment can have a big influence on how people process spatial information along their route (Carpman & Grant, 2002). The higher the number of environmental features and the more monotonous a city's characteristics, the more complex an environment becomes to navigate. In addition, the more complex an environment is, the more difficult it is for the navigator to notice and process the spatial information. For example, the study area used in Experiment 2 was more complex because it featured more pedestrian crossings as well as more pedestrian and vehicle traffic to watch out for, among other things. These additional tasks, which participants had to perform in addition to finding their way under complex, real-world conditions, could have led to stressful situations that increased mental workload and thus led to unnecessary map interactions and insufficient spatial knowledge acquisition. We would have to determine, therefore, whether the participants perceived the task of assisted route-following as being a difficult one.

5.4.3 Workload and task difficulty during navigation

The results from the NASA TLX questionnaire revealed that using any of the navigation system designs led to low mental and physical demands during the assisted navigation phase. The designs of the navigation systems thus fulfill the most important positive effect of automated assistance: namely, to keep the human workload low (Parasuraman & Riley, 1997). The results also confirm that the system designs led to a feeling of achievement and satisfaction. This is another intended effect for users of automated systems (Bainbridge, 1983; Janlert & Stolterman, 2017b). The results also show that the perceived workload did not differ between the participants that had spatially restricted or permanent access to the self-localization information from the navigation system. Lowering the level of system assistance did not influence the perceived workload during Phase

1. This insight supports the design solutions for future systems, which could work by turning off spatial information along the route in order to increase spatial knowledge acquisition, as proposed by Willis et al. (2009).

Another surprising result is that participants did not rate the unassisted return phase as more difficult even if they made more navigation errors. Participants received explicit feedback on their performance (e.g., "You took the wrong turn. Come back and make a new decision.") yet still rated their performance as good. This indicates that a high perceived mental workload and a frustrating navigation experience during the unassisted navigation phase does not necessarily result in a negative (low) overall rating of their performance. This indicates that pedestrians do not think that navigation errors are related to a bad performance. The overestimation of their performance might have been affected by the higher mental workload, temporal demand, effort, and frustration compared to the assisted navigation phase. This finding is particularly interesting when designing navigation systems that aim to account for workload from affective and emotional states (Pantic & Rothkrantz, 2003; Wunderlich & Gramann, 2018). We also have to ask whether the increased perceived workload from Phase 1 to Phase 2 results in distinct gaze behavior patterns.

5.4.4 Distinct gaze behavior patterns during both navigation phases

The results from the eye-tracking analysis confirmed a clear gaze behavior pattern during the assisted navigation phase, as found in Experiment 1, but also revealed an additional pattern during the unassisted phase. During the assisted phase, the initial longer fixation durations could indicate segments of higher cognitive functioning (Duchowski, 2017). After getting used to the navigation system and the environment, the participants spent shorter fixation durations in the following street segments. In Segments 5 and 6, the mean fixation durations of both groups increased and then decreased continuously along the rest of the route. This finding strengthens the argument of typical gaze behavior during assisted navigation. Interestingly, the results of the eye-tracking analysis also revealed a distinct pattern in the unassisted phase. This pattern is identical for all the groups from which data could be analyzed. A similar pattern along the

route across groups further indicates a relationship between gaze behavior and the surrounding environment, as suggested by Emo (2014) and Yates (2017). This suggests that such typical navigation patterns could facilitate real-world data processing for models predicting human behavior. However, some behaviors are different from those in Experiment 1.

In Experiment 2, I could not confirm dynamic behavior in a vertical direction (up and down) or stable behavior in a horizontal direction (left and right), like I could for Experiment 1. Reasons for this could be the increased complexity of the environment, such as having to look out for traffic and uneven ground, which could influence the gaze behavior, particularly in vertical directions. However, it is important to mention that the number of participants for the gaze analysis of Experiment 2 was rather low. As stated in Section 4.4, data availability is essential to identify gaze behavior patterns across groups. Unfortunately, this was not the case for the second experiment as the eye-tracking glasses were not able to record data for the majority of the participants. Therefore, the data was unable to determine whether there were any consistent behavioral patterns across all the participants like there were in Experiment 1.

5.4.5 Summary

The results of the second experiment using the WALK-AND-LEARN framework suggests that even navigation systems with spatially restricted access to self-localization information allow for efficient and effective navigation performance, while also having a low task workload. The participants gave a positive evaluation of the system designs, even expressing an unusual acceptance for a new design that restricts information access. Despite the fact that the designs allow for high navigation performance and provide good usability during the assisted phase, these systems could not support the users in acquiring sufficient spatial knowledge to find their same way back in Phase 2. The success rates were low across all the groups, which could be because of the increased number of map interactions and the added complexity of the environment compared to Experiment 1. In other words, this shows that the environment can have a profound influence on navigation behavior. As a result, the participants did not only make unnecessary decisions regarding map use but were also

distracted from paying attention to relevant features in the environment for safety reasons.

Chapter 6

GENERAL DISCUSSION

The goal of this thesis is to better understand the effect of varying the level of automation in navigation systems on human navigation behavior and spatial knowledge acquisition. In order to do this, I developed the WALK-AND-LEARN framework that assesses human navigation behavior and spatial knowledge acquisition with use-inspired scenarios in real-world environments. Below, I will discuss the main research question defined in Section 1.2 based on the findings described in Chapter 4 and Chapter 5. I will then put them in context to related work and then critically examine the possibilities and limitations of the empirical work. The main research question is as follows.

> How can the advantages of analog (human-centered) and automated (system-centered) navigation assistance be combined to ensure navigation efficiency without losing the ability to acquire spatial knowledge?

6.1 Equal efficiency and diverse spatial knowledge acquisition

My research reveals that it is possible to design a human-centered navigation system that can ensure a high level of navigation efficiency without losing the ability to acquire spatial knowledge. Previous studies have found that navigators find their way better when using navigation systems rather than using analog maps (Dickmann, 2012; W.-C. Lee & Cheng, 2008; Münzer et al., 2006), but they also

lose the skill to acquire spatial knowledge (Chen & Stanney, 1999; Gardony et al., 2013; Mondschein & Moga, 2018). I have demonstrated, in both experiments, that navigation systems with a human-centered design allow navigators to reach their destination as efficiently as when using navigation systems with a system-centered design. However, only those navigators with a human-centered navigation system acquired sufficient spatial knowledge to find their way back. Specifically, I found that active decision-making by the navigator yields differences in spatial knowledge acquisition in the real world.

Pedestrians with a navigation system that allows them to make own decisions relating to the traversed environment acquire sufficient spatial knowledge to find their way back compared to those that use a system that either restricts or takes away such decisions. The result suggests that active decision-making is the main component of active navigation and thus for acquiring spatial knowledge. Similar results were found in a virtual environment study by Bakdash et al. (2008). The task of selecting three landmarks in Experiment 1 not only gives the navigator a clear navigation goal along the route, besides reaching the destination at the end of the route but also allows them to self-govern and self-prioritize decisions. This has positive effects on cognitive processes, such as the allocation of attention (Guinote, 2017). With the freedom to control left to the navigator, a navigation system therefore deliberately structures the interactions between the system and the environment. Individually selected landmarks, collected with all human senses (see Section 6.4.1), serve as visual, structural, and semantic anchor points for spatial knowledge acquisition and recall. These landmarks do not exist in current navigation systems and should be considered as possible navigation instructions in future navigation system designs. This thesis confirms that an active decision-making task implemented within a navigation system design can fulfill a basic requirement of analog maps: that someone who uses navigation assistance should proactively allocate attention to their environment and should simultaneously focus cognitive effort to the task at hand in order to facilitate spatial knowledge acquisition (Kraft & Hurtienne, 2017; Parasuraman et al., 2000; Parush et al., 2007). However, this thesis also reveals that navigators do not always make rational navigation decisions.

Navigators who constantly use a map interface component to access spatial information may do this at the expense of spatial knowledge acquisition. If the

use of interface elements are unintended and are used in order to simply "do" something with the device, it can lead to a distraction from the reason why the device was being used in the first place, leading to a decrease in the process of acquiring knowledge (Guinote, 2017; Zacks & Tversky, 2001). To allow the human user to acquire specific information, system designers must implement the right amount of interactive decision-making into an assisting system (Janlert & Stolterman, 2017b), which is difficult. I partially account for that as participants were not allowed to decide switching form the Google Maps street layer to the satellite image. Participants were restricted to having one base map. Other tools to manipulate the map, such as zooming or panning, were constantly available to the navigator as these were found to be the most often used interactions when a digital map is used during real-world situations (Savino et al., 2020). The constantly available map tools led to an overuse of the system by the navigator, leading to poor judgement on their part as to how and when to use the system effectively and efficiently, and when to resist it. This confirms Montello's (2009) theory of "technological infantilization". I demonstrated that, for example, constantly pressing a button to show the blue dot on the map, or constantly zooming and rotating the map to get an updated map view disrupts the process of attending to relevant objects in the environment. Therefore, in order to determine the right amount of human decision-making and interaction with a navigation system, I implemented the design recommendation of getting information only at specific locations within the environment (O'Mara, 2019; Parasuraman & Riley, 1997; Willis et al., 2009; Wolter & Kirsch, 2017). Specifically, the system decides where to provide information on self-localization and allocation of attention if the navigator wishes to use it.

6.2 Context-aware information hinders spatial knowledge acquisition

This thesis reveals that navigation systems with location-aware information negatively affect spatial knowledge acquisition but without influencing navigation performance. A context-aware system tracks the position of navigators and triggers information as soon as the navigator enters a specific geographic area

(Rodriguez Garzon & Deva, 2014; Wawrzyniak & Hyla, 2016). The findings of the two experiments confirm that interactive interventions, such as context-dependent information services, can distract a navigator as they interrupt current activities and increase the user's attention on the system and away from the surroundings as a result (U. Lee et al., 2014; Pielot & Rello, 2017). Context-aware navigation system designs do not support navigators in actively making decisions and thus decrease spatial knowledge acquisition. An explanation for this is that users do not decide by themselves when to allocate their attention to the information on the system and when they allocate it to the environment; instead, they are forced to do so at locations they have no control over (Taylor et al., 2008). The result is a fragmentation of attention driven by the system (Gardony et al., 2013; Willis et al., 2009) that changes how humans attend to their environment (Parush et al., 2007). As information access from the system is restricted to specific spatial areas, the navigators need to get information between the spatially restricted information areas on their own. To do this, the participants either put in sufficient cognitive effort by e.g., remembering the next steps, or by updating their own position in the environment. Alternatively, they offloaded cognitive effort by interacting with the system (e.g., by changing the map scale with zoom interactions), and thus focused on the navigation system. The results of the experiments support the findings of other studies that suggest that humans usually choose the path of least cognitive effort, i.e. by constantly interacting with the navigation system (Gardony et al., 2013; Ishikawa et al., 2008; Willis et al., 2009). The available map interaction tools motivate the users to use them and to distract them from the necessary focus on the changing environmental context. The navigators' interactions with the map are also influenced by the structure of the traversed environment (Barsalou, 1988; Emo, 2014; Mondschein & Moga, 2018).

Participants interact more with the map when navigating in a more complex environment. A possible explanation for the surprisingly low success rates across groups in the second experiment might be that the complex environment distracted the participants from actively processing the relevant information from the environment and increased their interactions with the map instead. This explanation agrees with findings by Gardony et al. (2013) and Willis et al. (2009). The appearance, structure, and significance of the environment are

important for humans to process information (Carpman & Grant, 2002), but humans' attention capabilities are limited (Downs & Stea, 1973; Weisberg & Newcombe, 2018). While a complex and landmark-rich environment might seem to invite humans to actively attend to it, other aspects, such as crossing streets or walking on crowded sidewalks, focuses the navigators' attention on avoiding obstacles and moving objects rather than on relevant navigation information. Two facts indicate that navigators have too much unstructured access to information during navigation. First, more environmental features vie for the navigator's attention in highly complex environments (Janlert & Stolterman, 2017b). Second, additional map functionalities compete for attention in modern navigation systems and are not always reasonably used (Ishikawa et al., 2008). The skill of traditional cartographers is to specifically choose a graphical map design for a specific purpose (Slocum et al., 2009), which is not the case for modern navigation systems. Users of modern navigation systems have many types of map scales, layers of base maps, types of landmarks, numerous interactive elements, etc. available for all kinds of tasks and all kinds of transportation modes. This thesis shows that users of such systems do not seem to know how and when to use the system's tools in a meaningful way for the task at hand. As a result, humans lose the ability to acquire spatial knowledge. The findings of this work highlight the importance of more efficiently distributing decision-making on the allocation of attention between humans and navigation systems, and to support a design solution for a navigation system to implement user-centered decision-making (Willis et al., 2009) in different environments. Such designs thus address the problem of "technological infantilization" (Montello, 2009) by making the navigator think and reason when using the navigation system.

6.3 Partly automated navigation systems share cognitive processes between humans and systems

The approach of systematically structuring cognitive processes by varying human engagement proved to be a good method for designing partly automated

navigation assistance. All navigation system designs fulfill the goal of analog maps to guide humans efficiently and successfully from the start of their journey to their destination. According to Allen (1999) and Slocum et al. (2009), this is the main goal of using maps during navigation. Some navigation system designs even fulfill the more recent requirement of mobile maps: to help humans acquire spatial knowledge during navigation (Parush et al., 2007).

This thesis thus offers a novel approach to studying the advantages of analog and automated navigation assistance in system designs by systematically varying cognitive processes with the theory of the levels of automation put forward by Parasuraman et al. (2000). This thesis also builds on work by T. Martin et al. (1991) and Parasuraman et al. (2000) who stated the importance of evaluating automated processes in systems in order to justify their implementation. According to them, researchers should evaluate which tasks/processes should be automated by the system and which should be executed by the human user, as well as what effects automation has on human navigation behavior. To find an appropriate level of automation, each process during task execution should be individually evaluated. I applied this approach to two cognitive processes relevant to navigation: self-localization and allocation of attention. As stated in Sections 6.1 and 6.2, I can confirm that navigation systems have both intended and unintended effects on human behavior and spatial knowledge acquisition depending on how these cognitive processes are shared between the navigation system and navigator. Navigators using human-centered assistance acquired sufficient spatial knowledge to find their way back, while navigators using system-centered assistance acquired insufficient spatial knowledge. All systems ensured navigation efficiency and navigation effectiveness. These findings highlight the importance of studying modern, intelligent systems that act autonomously (e.g., context-adaptive) in providing information (Wolter & Kirsch, 2017), and support the argument that automated systems should ensure an interplay between the system and the user (Sheridan, 2002) without the system degrading the user's cognitive abilities (Brey, 2006).

The goal of intelligent systems is to perform tasks that humans would otherwise be doing themselves (Janlert & Stolterman, 2017b; Scerbo, 1996; Wolter & Kirsch, 2017). For example, humans using an analog map would make a decision whether and/or when to turn the map by 90 degrees when turning left at an intersection.

Navigators with an intelligent navigation system would not have to proactively make this decision, as a context-aware system will automatically adapt to the situation through system sensors and will automatically rotate the map for the navigator. However, the more a system automatically adapts to context (i.e. the environment and/or the person), the more important the data input from this context (Bainbridge, 1983; T. Martin et al., 1991). For example, if navigation systems of the future adapt to human cognitive functioning, system algorithms will depend on functioning human brain activity as a data source. To ensure that such intelligent systems support rather than hinder human skill development, it is essential to understand data that is collected during navigation tasks in-situ. The main reason for this is that the systems will learn from the data of the tasks for which such systems are designed. The WALK-AND-LEARN framework allows us to collect behavior data from navigators and knowledge acquisition during assisted and unassisted navigation tasks in real-world, outdoor environments.

6.4 WALK-AND-LEARN framework

Imagine that you follow a suggested route on a navigation system in an unknown city for about ten minutes. Do you think you would be able to retrace your steps without the navigation system?

As stated in the introduction to this thesis, use-inspired research enables researchers to examine data on human behavior in-situ under controlled experimental conditions. It allows researchers to collect data on tasks that happen in everyday life, and to better understand what (navigation) systems are actually designed and used for. Nevertheless, real-world navigation experiments are fewer in number compared to experiments in labs and virtual environments (Dai et al., 2018) but they provide high ecological validity (Kiefer et al., 2014).

I collected data from pedestrians in a real-world outdoor environment during an assisted route-following task and an unassisted route-reversal task. In Section 3.1.3, I specified the advantages that the WALK-AND-LEARN framework has over advanced traditional setups: participants use all their senses to actively learn with the assistance of a digital map, and actively test their spatial knowledge when retracing their steps to ensure a use-inspired and practical way of executing a real-world experiment. I will now critically examine these advantages based on

the two experiments conducted with the WALK-AND-LEARN framework. The following research question guides this evaluation.

> How valid is the approach from the empirical framework of an assisted and unassisted navigation phase for gathering useful data on pedestrian navigation behavior and spatial knowledge acquisition?

6.4.1 Use all human senses during learning and testing

Participants use all their human senses to recall their previously acquired knowledge in order to successfully navigate an urban environment. With an active learning and active testing phase, the framework accounts for the shortcomings of traditional setups that usually test participants in a passive manner (e.g., by using photos for image recognition tasks). The WALK-AND-LEARN framework allows humans to use all their senses during incidental learning of the route, and testing of spatial knowledge acquisition, and thus fulfills a recommendation for empirical studies suggested by O'Mara (2019). Participants are able to recall their acquired spatial knowledge from other senses as well as sight in navigation experiments. Being asked about what helped her to find the way back, one participant answered that the music from a coffee shop reminded her to turn at this particular intersection. Another successful navigator recognized the smell of flowers along the route. The use of sound and smell can trigger recognition only when the navigator is close to or right next to the respective landmarks. Such types of incidental structural landmarks recognized from senses other than vision would not be included in traditional laboratory experiments. The WALK-AND-LEARN framework accounts for a restriction of human senses in virtual environments, such as a restriction in the sense of smell that is presented in a recent study by Hamburger and Knauff (2019). They found that odors can affect the recognition of landmarks during navigation, but they also had to remove certain odors, such as gasoline, due to safety reasons within their indoor virtual environment. In experiments with the WALK-AND-LEARN framework, unpleasant odors, such as rotting vegetables from a container or gasoline at a car garage, could still serve as landmarks without restrictions due to safety reasons. In addition to the senses of hearing and smell, tactile

perception in combination with vision also serve as anchor points for spatial knowledge acquisition. Figures 4.1 (middle right) and 5.1 (bottom left and bottom right) show pavement characteristics, such as blind stripes or the cracks in the paving stones. Several participants highlighted that the characteristics of the ground, e.g., the texture of the pavement, helped them to recognize their environment during the route-reversal task. I therefore recommend including landmarks derived from all human senses in pedestrian navigation systems for pedestrians to support spatial knowledge acquisition for people with 20/20 vision, but also for those navigators who are visually impaired (Giudice, Walton, & Worboys, 2010). It is important to mention that the navigation systems designed in this thesis do not explicitly promote the sensory perception (except vision) of the environment. The perception with all senses is not integrated into the systems, but the observations reveal the fundamental difference in human perception between lab and real settings.

The framework does not reveal the type of knowledge participants use to find their route back. It does not include traditional tests to determine specific types of spatial knowledge, as identified by Siegel and White (1975). Perhaps participants remembered the route from the navigation system, or maybe they remembered specific landmarks after an auditory cue or recognized the environment by combining the cues perceived while walking back. The influencing factors of how to find the way back are difficult to disentangle, particularly as the framework requires that participants change their viewing direction between the learning and the testing phase. Cohen and Conway (2008) stated that learning a route in a forward direction and having to find the way back in the reverse direction is almost the same as navigating in an unfamiliar environment. The viewpoint of the navigator changes and recognition of objects has to be done from the opposite viewpoint. As this is a limitation of the empirical framework, I argue that this is what makes it a use-inspired scenario and proved to be achievable even yielding no errors by multiple participants in both experiments. However, pedestrian navigation comes with many individual characteristics, which are discussed below.

6.4.2 The consequences of individual locomotion on the egocentric view and information access

This thesis emphasizes that the individual path choices of pedestrians have significant impacts on human locomotion, gaze behavior, GPS signal strength, and respective data analyses. Locomotion is different for pedestrians and vehicles because the time and perspective to perceive and attend to objects in the environment varies due to velocity differences and varying spatial restrictions (i.e., pavement or road) (Gaisbauer & Frank, 2008). The distance from the middle of the street to a sidewalk makes a difference in terms of the field of egocentric view. While car drivers in urban environments have a more open field of view in their moving direction, pedestrians usually walk along sidewalks with a restricted view on at least on one side (caused by buildings, bushes/trees, parked trucks). The participants in my experiments walked on the sidewalks rather than in the middle of the street, as usually happens in lab experiments in virtual environments. The snapshots in Figures 4.1 (top two images) and 5.1 (middle left and top right) depict the typical views of pedestrians along the straight street segments. Walls, bushes, trees, or parked cars can restrict the view of pedestrians. This also has to be considered for navigation system designs to allow pedestrians to successfully match the information from the map to the environment from their current point of view, particularly as the participants are free to choose the side of the street for walking and the pedestrian crossing for crossing the street.

Individual walking choices result in different egocentric views along the same route, and might have an influence on spotting landmarks, avoiding traffic, or matching the map content to the environment (Aretz & Wickens, 1992; Lobben, 2004; Meilinger et al., 2012; Wang, 2017). This has implications for the design of future navigation systems and navigation data analysis methods that are based on spatial data models of the environment. The viewpoints of different navigation types change the perspective on and the interaction with the environment. This is particularly important if one is interested in a particular landmark in the environment, as seen from a specific point of view during navigation. For example, if a trajectory (taken from a street dataset) is used for a visibility analysis, the trajectory should be the one that pedestrians actually

walked, and not the center line of a street that a motorist might use. Alternatively, if a navigation system points to a global landmark (e.g., the Eiffel Tower), it should be seen from a pedestrian's actual point of view. To ensure the same view on this landmark, the instructions for the navigation task thus need to include clear statements on where exactly the participants should be walking, and where they should cross the streets. Such instructions take away the freedom of pedestrians to individually decide where to walk. They are prescriptive and would feel strange in real-world settings, and thus hinder use-inspired scenarios and respective experiences. With the WALK-AND-LEARN framework, the movement trajectory of a navigator does not influence the testing phase, as each participant can retrieve the path already taken during the learning phase. Each participant can thus reconstruct their own view of their environment, which in turn facilitates individual recall of incidentally acquired spatial knowledge. On the other hand, a free walking choice has an influence on the context-aware design of navigation systems in urban environments and on navigation gaze behavior.

The areas of context-aware access to information need to be quite large in order to be able to detect the navigator at their correct location and to provide the correct information on the respective area. The low level of accuracy in GPS signals for pedestrians in urban environments is a well-known problem (Schneider, Dreher, & Seidel, 2011). While cars that drive in the middle of a street receive accurate signals, pedestrians usually walk close to walls or in pedestrian-only streets where GPS signal is often limited. Therefore, where a person walks along the street is crucial for navigation systems to function automatically at the correct location and thus should particularly be considered when designing navigation assistance for pedestrians. The notifications to attend to landmarks (Experiment 1), the geofencing approach of spatially restricted access to self-localization information (Experiment 2), and the display of the self-localization information (i.e. the blue dot) all depend on the accuracy of the GPS signal. Weak satellite reception in cities results in slight shifts in the signal displayed on the map, and geofencing will thus suffer in precision. For this reason, the polygons used for spatial restrictions in the second experiment needed to be quite large in order to overcome the lack of accuracy of the GPS signal within narrow, urban streets. This methodological limitation might influence navigation behavior and spatial knowledge acquisition

because the number of fixations on the navigation system increases in order to get localization information from the navigation system but also represents a real-world problem for pedestrians.

The walking location also influences gaze behavior. While I annotated the first-person videos from the eye-tracking recordings, the number of gazes toward the pavement and surface features stood out. Human behavior during real-world navigation involves the combined effort of first seeing obstacles (e.g., protruding roots, pavement edges, traffic) and then visually processing this information (Montello, 2005) in order to avoid them. The video analysis confirmed that this basic locomotion behavior demands significant attention from urban navigators. This is similar to the results of an eye-tracking study by Simpson et al. (2018). With this thesis, I can demonstrate that navigators are distracted by two major elements from the environment. First, a navigation system distracts navigators from attending to the environment. Second, the environment that shapes pedestrian locomotion (e.g., pavement edges, pedestrian crossings, etc.) distracts navigators from attending to environmental features that are relevant for spatial knowledge acquisition. I could further identify a typical gaze behavior pattern during an assisted route-following task. Across both experiments and all navigation system designs, a specific wave pattern of fixation durations occurred. This might indicate typical behavior of allocation of attention along a route during a pedestrian navigation task in the real-world and needs further analysis.

I analyzed the participants' gaze behavior during both the learning and testing phases because research has found that navigation systems alter how humans allocate their attention to the environment and thus change their landmark selection for navigation (Gardony et al., 2013; Ishikawa et al., 2008; Parush et al., 2007; Taylor et al., 2008). The spatial segmentation method allows us to identify and compare behavior patterns across navigators, tasks, and spatial context. The method of segmenting the route at intersections is just one way of discretizing the continuous behavior data collected along the route. Other segmentation techniques (e.g., at turns) might lead to different findings. Although the method of spatial segmentation does not allow us to systematically identify what participants allocated their attention to during the experiment without manually annotating each fixation to an area of interest, it can generally tell us something about potential general gaze behaviors across groups in a

spatio-temporal context. However, if one participant crosses the street at a different pedestrian crossing to another participant, the reference points in the environment which annotate the data (e.g., the end of a crosswalk that marks the end of an intersection) might change, leading to additional work for the data analyst. Developments in automatic image recognition with machine learning will facilitate gaze analysis in the future (Wolf et al., 2018), and also, hopefully, for real-world mobile eye-tracking data. Still, the spatial segmentation method enables efficient data processing with real-world eye-tracking data, which is generally considered to be a challenging task (Goldberg & Kotval, 1999; Kiefer, Giannopoulos, Raubal, & Duchowski, 2017; Koletsis et al., 2017; Liao et al., 2017; Ohm et al., 2017). The development of such a method that allows for efficient analysis of gaze data in a complex spatial context, contributes to the knowledge gap of being able to relate human behavior to spatial context during navigation system use, as mentioned by Dai et al. (2018).

6.4.3 Execution of and feedback on the WALK-AND-LEARN framework

Part of the reason I developed the WALK-AND-LEARN framework was to simplify navigation studies for organizational purposes. The following research question guides this evaluation.

> How well does the execution of an outdoor experiment work within the WALK-AND-LEARN framework?

After conducting two experiments motivated by the proposed WALK-AND-LEARN framework, it became apparent that the sequence of instructions/setups, the learning and in-situ testing phases, and the questionnaires worked very well for all of the 107 participants tested. The time taken for physically walking a route twice and filling out short questionnaires (before, between, and after a navigation task) can be evaluated with a series of pilot tests. Such pilot tests are proved to work for an accurate sequence of consecutive scheduled participants, as the ending point of the testing phase is the starting point for the learning phase for the next participant.

Because the framework emphasizes a use-inspired experience, the real-world

approach leads to a certain positivity and understanding among participants and thus might have increased their interest in participating in my studies. The participants enjoyed the setup, understood the purpose of the study, and reflected on their own navigation behavior. Some of the comments that participants gave after the experiment (translated from the original German) are good examples of this.

- "I usually participate in lab experiments in which I am asked to do the same thing 100 times. It feels like they last for ages, and I never know what spotting a squared symbol within circled symbols has to do with everyday life. I would like to participate more often in such real-world experiments. That experiment felt like it passed within a second."
- "I have learned a lot about myself and my sense of orientation in this experiment. It was fun."
- "I could discover other things on the way back (unassisted phase) that I had missed during the assisted phase because I was focusing a lot on the map."
- "I hope you can improve the navigation system design so that I do not make similar, slightly embarrassing mistakes in the future."

Furthermore, the video data analysis and my experiences as a researcher during the studies gave me new insights into the social implications of outdoor studies, such as the curiosity of local residents regarding my experiments in their neighborhood. The large eye-tracking glasses attached with a cable to a backpack and the fact that I was following the participant attracted attention from passing pedestrians, motorists, and local residents. In addition, some of the pedestrians and restaurant owners wanted to know what this was all about, as they were concerned about being filmed. Situations like these demanded quick answers as the participants should not be able to walk too far ahead of the researcher and should not be disturbed while performing the actual navigation task. A prepared sentence to satisfy the curiosity of the people should always be at hand. Once they knew what my study was about, the level of support and understanding from the local community was noticeable. Since we received suspicious looks and questions about the purpose of walking the same route many times, the WALK-AND-LEARN

framework identifies a much-needed awareness of society to have experiments in their immediate surroundings. This is important for the people working within the study site (e.g., waiters), and the researcher, but not for the participants. This thesis provides initial findings on the social implications of using navigation systems that are, as yet, unknown (Huang et al., 2018).

Overall, this thesis used the WALK-AND-LEARN framework and was able to uncover new insights regarding data collection and data analysis of both components of navigation: locomotion and wayfinding. The main advantage of this thesis is that it deals with these two components of navigation in-situ. I can demonstrate that both components of navigation are influenced by the navigation task (Liao et al., 2019), navigation assistance (Dickmann, 2012; W.-C. Lee & Cheng, 2008; Münzer et al., 2006), the physical and social environment (Carpman & Grant, 2002; Lynch, 1960; Weisman, 1981), and the navigators themselves (Froehlich et al., 2019; O'Mara, 2019). It will be a challenge for future navigation research to fully understand these influencing factors in relation to each other and their impact on pedestrians' spatial knowledge acquisition.

Chapter 7

CONCLUSION

Navigation is an everyday activity for humans. Navigation tasks turn out to be a challenge, especially in unknown environments, and require mental effort and spatial skills both with and without assistance. Humans have been using spatial representations (e.g., maps) as assistance for a very long time (Wiener et al., 2009), yet the invention of automatic and increasingly intelligent (navigation) systems brings with it faster assistive but also hindering properties for humans and their skill development. On the one hand, map designs of automated navigation assistance increase navigation efficiency compared to analog map designs (Dickmann, 2012; W.-C. Lee & Cheng, 2008), while on the other hand, automated navigation assistance decreases humans' ability to acquire spatial knowledge (Parush et al., 2007; Willis et al., 2009). To date, little is known about how automatic (intelligent) navigation systems influence human behavior and cognitive processes, particularly for pedestrians in dynamic, real-world environments. The goal of this thesis is to better understand how partly automated navigation assistance influences human navigation behavior (e.g., navigation efficiency) and spatial knowledge acquisition in the real world, especially in urban environments.

7.1 Main findings and contributions

In this thesis, I can demonstrate how partly automated navigation assistance can be designed to ensure high navigation efficiency without the navigators losing their ability to acquire spatial knowledge during navigation, particularly when at

least one cognitive process is implemented with a low level of automation. The methodology of systematically analyzing cognitive processes between human-centered (a low level of automation) and system-centered (a high level of automation) designs provide new insights into how the advantages of analog and automated navigation assistance can be implemented in partly automated navigation systems. The analysis of the navigation behavior of people using navigation systems with various levels of automation contributes to the understanding of collaborative human-system interactions during navigation. Interactive maps provide many advantages in terms of facilitating navigation performance, but they also reveal disadvantages in terms of increased human distraction and resulting passiveness (W.-C. Lee & Cheng, 2008; Parush et al., 2007; Willis et al., 2009). Analyzing empirically collected data highlights that the design of navigation systems influences human navigation behavior (e.g., hesitations, map interactions) and respective cognitive processes (spatial knowledge acquisition). Specifically, I can demonstrate how navigators with a much higher active engagement in the navigation process can still achieve a high level of navigation efficiency while also acquiring incidental spatial knowledge. The implementation of a low level of automation in a navigation system design demands further analysis of pedestrians' acceptance for practical everyday use.

The thesis proposed applying geovisual analysis methods of experimental data on navigation behavior under highly ecologically valid conditions. The research provides evidence that navigators use all their senses to acquire and to recall incidental spatial knowledge when navigating in the real world. Given the lack of real-world studies, I developed and tested the WALK-AND-LEARN framework to efficiently collect and analyze pedestrian navigation behavior in-situ. The empirical framework allows navigators to use all of their senses, not just sight, during both the learning and testing phases of a navigation experiment. The framework addresses the importance of self-locomotion (e.g., walking) on navigation behavior and spatial learning processes (O'Mara, 2019), and the shortcomings of studies conducted with the highest ecological validity (Kiefer et al., 2014). The two navigation experiments applying the WALK-AND-LEARN framework confirm results on finding the return path of a lab experiment by Karimpur et al. (2016) in the real world. The high ecological validity of the two experiments also revealed challenges for data analysis. On the

one hand, pedestrians have a great deal of freedom in where to walk along the route and where to cross streets, but on the other hand, they are restricted to walking along sidewalks that are bordered by linear features (e.g., hedges, walls, etc.) that restrict the egocentric field of view while walking. The structure and characteristics of an environment thus shape human pedestrian behavior, meaning that these findings are inevitable for the design of empirical research and its analysis methods. Experiments that aim for a higher ecological validity should consider these findings, in order to imitate a more realistic navigation experience for participants. Additionally, I have demonstrated that such a framework allows for efficient execution of experiments in practice, and for reproducible applications in other study areas.

The outcome of this thesis further highlights the importance of research across many fields because the design of human-centered navigation systems requires cognitive, technical, and spatial expertise. I analyzed cognitive processes with a systematic approach usually applied to manufacturing systems and examined pedestrians' physical and cognitive behavior in a geographic context. The basis for this work builds on empirical findings from navigation studies in the lab and in virtual and real-world environments on system automation, spatial human behavior, and spatial cognition. The interdisciplinary approach opened interesting discussions and collaborations, and led to an acceptance of thematic and methodological findings between a diverse range of research fields (see List of Publications A).

Finally, the planning of a prospectively autonomous and smart city that ensures an attention-seeking, attractive, safe, and healthy society should consider every aspect of human behavior and skill development necessary for everyday activities. The thesis emphasizes the importance of empirical research on navigation with pedestrians in urban environments. Specifically, I studied the relationship between cognitive processes that are executed by the system (reduced effort by the human navigator) or by the navigator (reduced assistance from the system) to better understand human navigation behavior and spatial skill development such as incidental spatial knowledge acquisition. The work contributes to the understanding of human navigation behavior with automatic navigation (intelligent) systems. The data sources of future navigation systems will be the collected data on human navigation behavior and human spatial skills

that will allow for personalized and individualized information depictions (Ballatore & Bertolotto, 2015). The data will be collected, processed, and passed on at anytime, anywhere, for anybody and anything (Huang et al., 2018). Therefore, more research is needed to understand the navigation behavior data and the impact of such location-based services and systems on human decision making and navigation behavior in order to ensure a smart, healthy society within a digitally interconnected world.

7.2 Future research

I focused on the advantages of analog (human-centered) and automated (system-centered) navigation assistance that can be combined to ensure navigation efficiency without losing the skill to acquire spatial knowledge. Therefore, I developed the WALK-AND-LEARN framework in order to test pedestrian behavior and spatial knowledge acquisition in real-world environments. The findings of this thesis provide the following insights for future research.

7.2.1 Navigation system design with human-centered automation

In the two experiments, I implemented four out of the ten levels of automation (Parasuraman et al., 2000) with two cognitive processes relevant during navigation. The findings showed that the combination of the levels of automation and the cognitive processes in navigation systems matter for testing the participants in-situ. Other levels of automation should be analyzed to gain a deeper understanding of the implications of navigation system designs on human behavior and spatial knowledge acquisition. Further research will help to better understand the influence of the level of automation in navigation systems on human behavior and spatial knowledge acquisition.

The experiments revealed that poor GPS signal in dense urban environments hinders smart and precise system automation. The technical improvement of the navigation systems for pedestrians would have been a big effort, which I did not operate. Developing sensing technology in smart cities will be available at any

place and at any time for anyone and for help with any task and might therefore solve this problem for future system designs (Huang et al., 2018). Technical developments in such dense urban areas will improve the accuracy of GPS signals, or alternative networks will allow for the smart implementation of fine-grained geofences to further analyze spatially restricted access to information from the navigation system (Karimi, Zimmerman, Ozcelik, & Roongpiboonsopit, 2009). I have recorded data on the precision of GPS signals for both experiments, but have not included it in the analysis. Precision in location technology can more easily account for the design solutions of getting assistance from the navigation system at specific locations, as suggested by Willis et al. (2009), because accurate information from the navigation system might decrease map interactions, and thus increase attention on the traversed environment. Precision in automated navigation assistance might help to better understand incidental spatial knowledge acquisition of navigators in real-world urban environments.

Another aspect to consider for future research on automatic navigation systems is the cartographic design of the digital map. Two main design characteristics build the basis for future research: the design interface and the depiction of the environment on a mobile map (Griffin et al., 2017).

In this thesis, I focused on map tool interactions, button presses, and keyboard interactions using touch. Research on future human-system interactions also needs to include multi-modal interaction technologies (e.g., a combination of voice and touch interactions) and the physiological responses that can adapt navigation instructions to environmental and user contexts (Pantic & Rothkrantz, 2003; Wunderlich & Gramann, 2018; Zhou et al., 2015). To better understand the importance of allocation of attention during spatial knowledge acquisition, one could also see if voice-commands can ultimately replace touch interactions. For example, if the landmarks that participants either had to select, or which they received as a notification in Experiment 1, could possibly be implemented with voice recordings instead of written text. Such systems would also allow visually impaired people to access navigation information and would contribute to understanding applied human-system interaction for a more diverse user group (Riehle, Lichter, & Giudice, 2008).

Moreover, the map display included a base map of a street network, although many of the participants mentioned that they would have preferred the satellite

image. This is a constraint on the use-inspired argument for the WALK-AND-LEARN framework. A button to change the base map could easily be implemented and its use could be tested in a future study. In this work, context-dependent systems did not result in the acquisition of sufficient spatial knowledge to find the way back. Testing other visual variables for notifications on relevant landmarks (e.g., images, or icons) are another way to implement automated, context-dependent cartographic design solutions for spatial knowledge acquisition. Further research could also consider how an icon or a photo of a landmark could change the navigation performance of people retracing their steps, or whether a change in the type of notification from text to voice could increase spatial knowledge acquisition. Experiments that vary the type of interaction, the precision, and timelines of context-dependent information, and the type of base maps or map symbols, will shed more light on targeted cartographic design solutions for automatic navigation systems used during real-world navigation tasks in different environments and for different navigation tasks. Additionally, the designs of experiments that test the influence of adaptive map content based on emotional state, cognitive activity, spatial ability, and experience of the navigator on human navigation behavior and incidental spatial knowledge acquisition can help to better design human-centered navigation systems.

7.2.2 Ecologically valid research in complex environments

In the tested route-following task, the WALK-AND-LEARN framework assessed incidental learning. The task of following a route is just one of many navigational contexts where humans use navigation systems for assistance. The framework could also change the first phase to a route-planning task, which represents a similar use-inspired scenario. The downside of such a task is that the individual route choices would not allow for a behavior comparison on gaze and map interaction across participants and across space, as the individual route choices would be diverse. Nevertheless, the framework can easily be adjusted and reproduced.

Each participant experiences a slightly different traversed environment, e.g., with traffic, or with other people around, at different times of the day with different

weather conditions. The weather and time of day also influence the perception and attention allocation to the environment (e.g., shadows, traffic). Conditions can be considered stable if the learning and testing phase are within half an hour of each other, but the conditions can change rapidly between participants, and this cannot be controlled for, unlike in a virtual environment experiment set up. Leaves on trees, smells, wind, and temperatures depending on the season might also have influenced on human navigation behavior and spatial knowledge acquisition (Hamburger & Knauff, 2019). With the development of sensor technology, this data can also be collected during the experiment. Additional studies for future system designs are needed to gain a deeper understanding of the influence of the environment on attention behavior and spatial knowledge acquisition during the assisted navigation phase, as well as the navigation errors that (might) happen during the unassisted route-reversal phase.

The results of this work showed differences in spatial knowledge acquisition based on the complexity of the environment, even if the participants used similar levels of automation in navigation system designs. Partly automated navigation systems ensured, to some extent, the acquisition of spatial knowledge in environments with low complexity, although we need to know as how navigation systems can be designed to support spatial knowledge acquisition in complex environments. The significant influence of the environment on the allocation of attention and spatial knowledge acquisition for pedestrians is an important finding of this empirical work. Therefore, the complexity of the environment has to be taken into account for the design of future partly automated navigation systems. I therefore add another dimension to Figure 1.1 (presented in Chapter 1), which is depicted in Figure 7.1. I did not find a definition of the complexity of an environment and so I used my own description for it. To further evaluate the framework's potential and to understand the influence of the environment more deeply, it is important to apply it to other experiments in the real-world, and within labs and virtual environments.

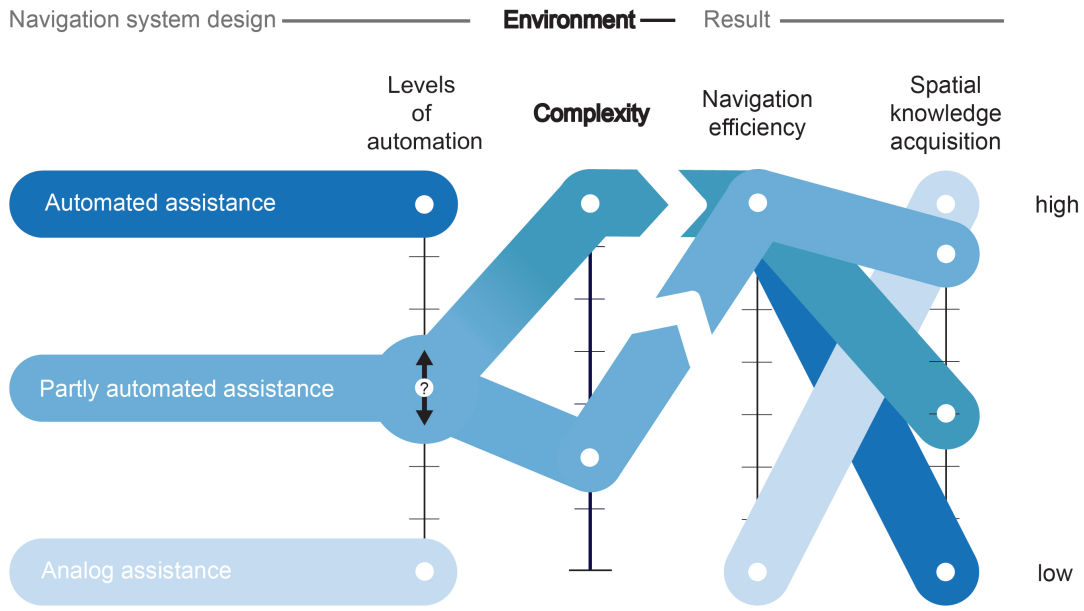

Figure 7.1: The complexity of the environment, e.g., traffic or ground characteristics, did not affect navigation efficiency but did affect spatial knowledge acquisition. This dimension is important when considering how to better understand the results of spatial knowledge acquisition in future real-world and lab navigation experiments.

7.2.3 Methodology and technology for the collection and analysis of data on navigation behavior

The data collected within the empirical framework allows for further analyses and method development. First, human behavior with the interactive map revealed both spatial and individual differences. Further analysis of the sequence, location, spatial clustering and trajectories of map interactions would be worthwhile. One reason for this is that map interactions will have to be understood for intelligent navigation systems to support a person's active engagement in the task at hand, and to automatically adapt to context to ensure cognitive skill development. Combining the map interactions with locomotion behavior could reveal as yet unknown spatio-temporal behavior patterns during real-world navigation.

Second, the methodology of spatial segmentation of mobile eye-tracking data revealed interesting gaze behavior patterns during both empirical phases without

manually annotating each fixation to an area of interest. However, the possibilities of the methodology in understanding these patterns and their relationship to environmental features still need further exploration, such as with automatic matching of navigation behavior data and the spatial data of the surrounding environment. The analysis of gaze behavior at specific landmarks, near to an intersection, and at street crossings might better explain the navigation errors made during the unassisted navigation phases. The gaze data could thus be used to develop a computational model of predicting navigation errors relative to environmental features.

Third, data on environmental characteristics (e.g., pedestrian crossings, landmarks), moving objects (e.g., cars), and the time of day (e.g., shadows) collected with sensor technology in a smart city could also be analyzed in order to recommend study areas with high levels of experimental control in the real world. The structure and features in a real-world test environment should be systematically analyzed in further experiments as they are found to influence information processing (Carpman & Grant, 2002) and could influence map interaction behavior and spatial knowledge acquisition, as found in this empirical study. Therefore, it is important to collect as much environmental information as possible in order to better understand the potential influences of the surrounding environment and its influence on human navigation behavior.

I developed navigation systems with various levels of automation, but with a focus on humans using their eyes. Pedestrians increasingly depend on vision to be aware of moving objects (e.g., electric vehicles). Such vehicles are intentionally designed to be silent which leads to possible safety issues for visually impaired people or for those who are otherwise distracted (e.g., by attending to navigation system). Automatic navigation systems are thus of great interest to people's security and for people with disabilities (Giudice et al., 2010). The framework should also be tested for hearing, sensing, and smelling in order to collect navigation information in real-world environments. Additionally, previous research has established that gender (Hegarty et al., 2006; Hund & Gill, 2014; Nazareth et al., 2019), individual differences such as spatial rotation ability (Hegarty et al., 2006) and sense of direction (Burte & Montello, 2017) influence spatial knowledge acquisition. However, it is not currently known how these factors interact with pedestrians' navigation system behavior (e.g., map

interactions) and spatial knowledge acquisition in real-world environments, and how they may cause problems when designing future navigation systems.

REFERENCES

Allen, G. L. (1999). Cognitive Abilities in the Service of Wayfinding: A Functional Approach. *Professional Geographer*, *51*(4), 554–561. doi: 10.1111/0033-0124.00192

Allen, G. L. (2000). Principles and Practices for Communicating Route Knowledge. *Applied Cognitive Psychology*, *14*(4), 333–359. doi: 10.1002/1099-0720(200007/08)14:4<333::AID-ACP655>3.0.CO;2-C

Appleyard, D. (1970). Styles and methods of structuring a city. *Environment and Behavior*, *2*(1), 100–117. doi: 10.1177/001391657000200106

Aretz, A. J., & Wickens, C. D. (1992). The Mental Rotation of Map Displays. *Human Performance*, *5*(4), 303–328. doi: 10.1207/s15327043hup0504_3

Bainbridge, L. (1983). Ironies of Automation. *Automatica*, *19*(6), 775–779. doi: 10.1016/0005-1098(83)90046-8

Bakdash, J. Z., Linkenauger, S. A., & Proffitt, D. (2008). Comparing Decision-Making and Control for Learning a Virtual Environment: Backseat Drivers Learn Where They are Going. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *52*(27), 2117–2121. doi: 10.1177/154193120805202707

Ballatore, A., & Bertolotto, M. (2015). Personalizing maps. *Communications of the ACM*, *58*(12), 68–74. doi: 10.1145/2756546

Barsalou, L. (1988). The content and organization of autobiographical memories. In U. Neisser & E. Winograd (Eds.), *Remembering reconsidered: Ecological and traditional approaches to the study of memory* (pp. 193–243). Cambridge, UK: Cambridge University Press.

Baudisch, P., & Rosenholtz, R. (2003). Halo: a Technique for Visualizing Off-Screen Locations. In *Proceedings of the sigchi conference on human factors in computing systems - chi '03* (pp. 481–488). New York, USA: ACM.

Bécu, M., Sheynikhovich, D., Tatur, G., Agathos, C. P., Bologna, L. L., Sahel, J. A., & Arleo, A. (2019). Age-related preference for geometric spatial cues during real-world navigation. *Nature Human Behaviour*. doi: 10.1038/s41562-019-0718-z

Berlin, I. (1969). Two concepts of liberty. In I. Berlin (Ed.), *Four essays on liberty*

(pp. 118–172). Oxford, UK: Oxford University Press.

Bertel, S., Dressel, T., Kohlberg, T., & von Jan, V. (2017). Spatial knowledge acquired from pedestrian urban navigation systems. In *Proceedings of the 19th international conference on human-computer interaction with mobile devices and services.* New York, USA: ACM. doi: 10.1145/3098279.3098543

Bevan, N. (2001). International standards for HCI and usability. *International Journal of Human Computer Studies*, *55*(4), 533–552. doi: 10.1006/ijhc.2001.0483

Blascheck, T., Kurzhals, K., Raschke, M., Burch, M., Weiskopf, D., & Ertl, T. (2014). State-of-the-Art of Visualization for Eye Tracking Data. In R. Borgo, R. Maciejewski, & I. Viola (Eds.), *Eurovis - stars.* The Eurographics Association. doi: 10.2312/eurovisstar.20141173

Block, R. A. (1998). Psychological Time and the Processing of Spatial Information. In M. J. Egenhofer & R. G. Golledge (Eds.), *Spatial and temporal reasoning in geographic information systems* (pp. 119–130). New York: Oxford University Press.

Brey, P. (2006). Freedom and Privacy in Ambient Intelligence. *Ethics and Information Technology*, *7*(3), 157–166. doi: 10.1007/s10676-006-0005-3

Burigat, S., & Chittaro, L. (2016). Passive and active navigation of virtual environments vs. traditional printed evacuation maps: A comparative evaluation in the aviation domain. *International Journal of Human Computer Studies*, *87*, 92–105. doi: 10.1016/j.ijhcs.2015.11.004

Burnett, G. E., & Lee, K. (2005). The Effect of Vehicle Navigation Systems on the Formation of Cognitive Maps. In G. Underwood (Ed.), *Traffic and transport psychology: theory and application : proceedings of the icttp 2004* (pp. 407–418). Amsterdam: Elsevier. doi: 10.1016/b978-008044379-9/50188-6

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). doi: 10.1186/s41235-017-0057-4

Carpman, J. R., & Grant, M. A. (2002). Wayfinding: A broad view. In R. B. Bechtel & A. Churchman (Eds.), *Handbook of environmental psychology* (pp. 427–442). Hoboken, NJ, US: John Wiley & Sons Inc.

Chen, J. L., & Stanney, K. M. (1999). A theoretical model of wayfinding in virutal environments: Proposed strategies for navigational aiding. *Presence: Teleoperators and Virutal Environments*, *8*(6), 671–685.

Cheverst, K., Mitchell, K., & Davies, N. (2001). Investigating Context-aware Information Push vs. Information Pull to Tourists. In *Proceedings of mobile hci 2001.*

Chrastil, E. R., & Warren, W. H. (2012). Active and passive contributions to

spatial learning. *Psychonomic Bulletin and Review*, *19*(1), 1–23. doi: 10.3758/s13423-011-0182-x

Chung, J., Pagnini, F., & Langer, E. (2016). Mindful navigation for pedestrians: Improving engagement with augmented reality. *Technology in Society*, *45*, 29–33. doi: 10.1016/j.techsoc.2016.02.006

Cohen, G., & Conway, M. A. (2008). *Memory in the real world* (3rd ed.). New York, NY, US: Psychology Press.

Couclelis, H., Golledge, R. G., Gale, N., & Tobler, W. (1987). Exploring the anchor-point hypothesis of spatial cognition. *Journal of Environmental Psychology*, *7*(2), 99–122. doi: 10.1016/S0272-4944(87)80020-8

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 and Computation*, *19*(3), 190-219. doi: 10.1080/13875868.2019.1569016

Dahmani, L., & Bohbot, V. D. (2020). Habitual use of GPS negatively impacts spatial memory during self-guided navigation. *Scientific Reports*, *10*(1), 6310. doi: 10.1038/s41598-020-62877-0

Dai, R., Thomas, A. K., & Taylor, H. A. (2018). When to look at maps in navigation: metacognitive control in environment learning. *Cognitive Research: Principles and Implications*, *3*(36). doi: 10.1186/s41235-018-0130-7

De Cock, L., Michels, R., Viaene, P., De Wulf, A., Ooms, K., Vanhaeren, N., ... De Maeyer, P. (2019). Comparing written and photo-based indoor wayfinding instructions through eye fixation measures and user ratings as mental effort assessments. *Journal of Eye Movement Research*, *12*(1). doi: 10.16910/jemr.12.1.1

Denis, M., Michon, P.-E., & Tom, A. (2007). Assisting Pedestrian Wayfinding in Urban Settings: Why References to Landmarks are Crucial in Direction-Giving. In G. Allen (Ed.), *Applied spatial cognition: From research to cognitive technology* (pp. 25–51). Mahwah, NJ: Lawrence Erlbaum.

Dickmann, F. (2012). City Maps Versus Map-Based Navigation Systems - An Empirical Approach to Building Mental Representations. *The Cartographic Journal*, *49*(1), 62–69. doi: 10.1179/1743277411y.0000000018

Dillemuth, J. (2005). Map Design Evaluation for Mobile Display. *Cartography and Geographic Information Science*, *32*(4), 285–301. doi: 10.1559/152304005775194773

Downs, R. M., & Stea, D. (1973). *Image and Environment - Cognitive Mapping and Spatial Behavior*. Chicago: Aldine Transaction.

Duchowski, A. T. (2017). *Eye Tracking Methodology*. London: Springer International Publishing.

Duckham, M., Winter, S., & Robinson, M. (2010). Including Landmarks in Routing Instructions. *Journal of Location Based Services*, *4*(1), 28-52. doi: 10.1080/17489721003785602

Ekstrom, R. B., French, J. W., Harman, H. H., & Dermen, D. (1976). *Manual for the Kit of Factor-Referenced Cognitive Tests*. Princeton, NJ: Educational Testing Service.

Emo, B. (2014). Seeing the Axial Line: Evidence from wayfinding experiments. *Behavioral sciences*, *4*(3), 167–180. doi: 10.3390/bs4030167

Fabrikant, S. I., Rebich-Hespanha, S., Andrienko, N., Andrienko, G., & Montello, D. R. (2008). Novel Method to Measure Inference Affordance in Static Small-Multiple Map Displays Representing Dynamic Processes. *The Cartographic Journal*, *45*(3), 201–215. doi: 10.1179/000870408x311396

Field, A., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. London, UK: Sage Publications Ltd.

Freundschuh, S. (2009). Map Perception and Cognition. In R. Kitchin & N. Thrift (Eds.), *International encyclopedia of human geography* (pp. 334–338). Oxford: Elsevier. doi: 10.1016/b978-008044910-4.00044-4

Froehlich, J. E., Brock, A. M., Caspi, A., Guerreiro, J., Hara, K., Kirkham, R., ... Tannert, B. (2019). Grand challenges in accessible maps. *Interactions*, *26*(2), 78–81. doi: 10.1145/3301657

Gaisbauer, C., & Frank, A. U. (2008). Wayfinding Model For Pedestrian Navigation. In *11th agile international conference on geographic information science* (pp. 1–9). University of Girona, Spain.

Gale, N., Golledge, R. G., Pellegrino, J. W., & Doherty, S. (1990). The acquisition and integration of route knowledge in an unfamiliar neighborhood. *Journal of Environmental Psychology*, *10*(1), 3–25. doi: 10.1016/S0272-4944(05)80021-0

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. doi: 10.1080/13875868.2013.792821

Gibson, J. J. (1962). Observations on active touch. *Psychological Review*, *69*(6), 477–491. doi: 10.1037/h0046962

Giudice, N. A., Walton, L. A., & Worboys, M. (2010). The informatics of indoor and outdoor space: A research agenda. In *Isa 2010 - proceedings of the 2nd acm sigspatial international workshop on indoor spatial awareness* (pp. 47–53). New York, NY, USA: ACM. doi: 10.1145/1865885.1865897

Gladwin, T. (1970). *East is a Big Bird: Navigation and Logic on the Pulawat Atoll*. Cambridge, MA: Harvard University Press.

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. doi: 10.1007/s10707-019-00344-3

Goldberg, J. H., & Kotval, X. P. (1999). Computer interface evaluation using eye movements: Methods and constructs. *International Journal of Industrial Ergonomics*, *24*(6), 631–645. doi: 10.1016/S0169-8141(98)00068-7

Golledge, R. G., & Stimson, R. J. (1997). *Spatial behavior: a geographic perspective*. New York, USA: The Guilford Press.

Gramann, K., Hoepner, P., & Karrer-Gauss, K. (2017). Modified navigation instructions for spatial navigation assistance systems lead to incidental spatial learning. *Frontiers in Psychology*, *8*, 193. doi: 10.3389/fpsyg.2017.00193

Griffin, A. L., White, T., Fish, C., Tomio, B., Huang, H., Sluter, C. R., ... Picanço, P. (2017). Designing across map use contexts: a research agenda. *International Journal of Cartography*, *3*(sup1), 90–114. doi: 10.1080/23729333.2017.1315988

Guinote, A. (2017). How Power Affects People: Activating, Wanting, and Goal Seeking. *Annual Review of Psychology*, *68*(1), 353–381. doi: 10.1146/annurev-psych-010416-044153

Hamburger, K., & Knauff, M. (2019). Odors Can Serve as Landmarks in Human Wayfinding. *Cognitive Science*, *43*(11), e12798. doi: 10.1111/cogs.12798

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.), *Human mental worklaod, advances in psychology* (Vol. 52, pp. 139–183). Amsterdam: North-Holland Press.

Haupt, J., Van Nes, N., & Risser, R. (2015). Look where you have to go! A field study comparing looking behaviour at urban intersections using a navigation system or a printed route instruction. *Transportation Research Part F: Traffic Psychology and Behaviour*, *34*, 122–140. doi: 10.1016/j.trf.2015.07.018

Hegarty, M., Montello, D. R., Richardson, A. E., Ishikawa, T., & Lovelace, K. (2006). Spatial abilities at different scales: Individual differences in aptitude-test performance and spatial-layout learning. *Intelligence*, *34*(2), 151–176. doi: 10.1016/j.intell.2005.09.005

Hirtle, S. C., & Hudson, J. (1991). Acquisition of spatial knowledge for routes. *Journal of Environmental Psychology*, *11*(4), 335–345. doi: 10.1016/S0272-4944(05)80106-9

Hirtle, S. C., & Raubal, M. (2013). Many to many mobile maps. In M. Raubal, D. M. Mark, & A. U. Frank (Eds.), *Cognitive and linguistic aspects of geographic space. lecture notes in geoinformation and cartography* (pp. 141–157). Springer Berlin Heidelberg. doi: 10.1007/978-3-642-34359-9_8

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & van de Weijer, J. (2011). *Eye Tracking: A Comprehensive Guide To Methods And Measures*. Oxford: Oxford University Press.

Huang, H., Gartner, G., Krisp, J. M., Raubal, M., & Van de Weghe, N. (2018). Location based services: ongoing evolution and research agenda. *Journal of Location Based Services*, *12*(2), 63–93. doi: 10.1080/17489725.2018.1508763

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. doi: 10.1559/15230406392107

Hund, A. M., & Gill, D. M. (2014). What constitutes effective wayfinding directions: The interactive role of descriptive cues and memory demands. *Journal of Environmental Psychology*, *38*, 217–224. doi: 10.1016/j.jenvp.2014.02.006

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

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. doi: 10.1016/j.jenvp.2007.09.002

Ishikawa, T., & Takahashi, K. (2013). Relationships between Methods for Presenting Information on Navigation Tools and Users' Wayfinding Behavior. *Cartographic Perspectives*, *75*, 17–28. doi: 10.14714/CP75.82

Janlert, L.-E., & Stolterman, E. (2017a). The Meaning of Interactivity - Some Proposals for Definitions and Measures. *Human-Computer Interaction*, *32*(3), 103–138. doi: 10.1080/07370024.2016.1226139

Janlert, L.-E., & Stolterman, E. (2017b). *Things that keep us busy: the elements of interaction*. Cambridge, MA: The MIT Press.

Javadi, A. H., Emo, B., Howard, L. R., Zisch, F. E., Yu, Y., Knight, R., ... Spiers, H. J. (2017). Hippocampal and prefrontal processing of network topology to simulate the future. *Nature Communications*, *8*(14652). doi: 10.1038/ncomms14652

Johansson, G. (1989). Stress, Autonomy, and the Maintenance of Skill in Supervisory Control of Automated Systems. *Applied Psychology*, *38*(1), 45–56. doi: 10.1111/j.1464-0597.1989.tb01373.x

Karimi, H. A., Zimmerman, B., Ozcelik, A., & Roongpiboonsopit, D. (2009). SoNavNet: A Framework for Social Navigation Networks. In *Proceedings of*

the 2009 international workshop on location based social networks - lbsn '09 (pp. 481–488). New York, USA: ACM.

Karimpur, H., Röser, F., & Hamburger, K. (2016). Finding the return path: Landmark position effects and the influence of perspective. *Frontiers in Psychology*, *7:1956*. doi: 10.3389/fpsyg.2016.01956

Kaulich, T., Heine, T., & Kirsch, A. (2017). Indoor Localisation with Beacons for a User-Friendly Mobile Tour Guide. *KI - Künstliche Intelligenz*, *31*(3), 239–248. doi: 10.1007/s13218-017-0496-6

Kiefer, P., Giannopoulos, I., Anagnostopoulos, V. A., Schöning, J., & Raubal, M. (2017). Controllability matters: The user experience of adaptive maps. *GeoInformatica*, *21*(3), 619–641. doi: 10.1007/s10707-016-0282-x

Kiefer, P., Giannopoulos, I., & Raubal, M. (2014). Where am I? Investigating map matching during self-localization with mobile eye tracking in an urban environment. *Transactions in GIS*, *18*(5), 660–686. doi: 10.1111/tgis.12067

Kiefer, P., Giannopoulos, I., Raubal, M., & Duchowski, A. (2017). Eye tracking for spatial research: Cognition, computation, challenges. *Spatial Cognition and Computation*, *17*(1-2), 1–19. doi: 10.1080/13875868.2016.1254634

Klippel, A., Hirtle, S., & Davies, C. (2010). You-are-here maps: Creating spatial awareness through map-like representations. *Spatial Cognition and Computation*, *10*(2-3), 83–93. doi: 10.1080/13875861003770625

Koletsis, E., van Elzakker, C. P. J. M., Kraak, M.-J., Cartwright, W., Arrowsmith, C., & Field, K. (2017). An investigation into challenges experienced when route planning, navigating and wayfinding. *International Journal of Cartography*, *3*(1), 4–18. doi: 10.1080/23729333.2017.1300996

Kool, W., McGuire, J. T., Rosen, Z. B., & Botvinick, M. M. (2010). Decision Making and the Avoidance of Cognitive Demand. *Journal of Experimental Psychology: General*, *139*(4), 665–682. doi: 10.1037/a0020198

Kraft, J. F., & Hurtienne, J. (2017). Transition animations support orientation in mobile interfaces without increased user effort. In *Proceedings of the 19th international conference on human-computer interaction with mobile devices and services* (pp. 1–6). New York, NY, USA: ACM. doi: 10.1145/3098279.3098566

Kray, C., Elting, C., Laakso, K., & Coors, V. (2003). Presenting route instructions on mobile devices. In *Proceedings of the 8th international conference on intelligent user interfaces* (pp. 117–124). New York, New York, USA: ACM. doi: 10.1145/604045.604066

Krüger, A., Aslan, I., & Zimmer, H. (2004). The Effects of Mobile Pedestrian Navigation Systems on the Concurrent Acquisition of Route and Survey Knowledge. In S. Brewster & M. Dunlop (Eds.), *Mobile human-computer interaction - mobile hci 2004. mobile hci 2004. lecture notes in computer*

science (Vol. 3160, pp. 446–450). Springer, Berlin, Heidelberg. doi: 10.1007/978-3-540-28637-0_54

Kurzhals, K., Hlawatsch, M., Seeger, C., & Weiskopf, D. (2017). Visual Analytics for Mobile Eye Tracking. *IEEE Transactions on Visualization and Computer Graphics*, *23*(1), 301–310. doi: 10.1109/TVCG.2016.2598695

Lander, C., Herbig, N., Löchtefeld, M., Wiehr, F., & Krüger, A. (2017). Inferring landmarks for pedestrian navigation from mobile eye-tracking data and Google Street View. In *Proceedings of the 2017 chi conference extended abstracts on human factors in computing systems* (pp. 2721–2729). New York, NY, USA: ACM. doi: 10.1145/3027063.3053201

Laugwitz, B., Held, T., & Schrepp, M. (2008). Construction and Evaluation of a User Experience Questionnaire. In A. Holzinger (Ed.), *Hci and usability for education and work, usab 2008. lecture notes in computer science* (Vol. 5298, pp. 63–76). Springer, Berlin, Heidelberg. doi: 10.1007/978-3-540-89350-9_6

Lee, U., Lee, J., Ko, M., Lee, C., Kim, Y., Yang, S., ... Song, J. (2014). Hooked on smartphones: An exploratory study on smartphone overuse among college students. In *Proceedings of the sigchi conference on human factors in computing systems* (pp. 2327–2336). New York, NY, USA: ACM. doi: 10.1145/2556288.2557366

Lee, W.-C., & Cheng, B.-W. (2008). Effects of using a portable navigation system and paper map in real driving. *Accident Analysis and Prevention*, *40*(1), 303–308. doi: 10.1016/j.aap.2007.06.010

Liao, H., Dong, W., Huang, H., Gartner, G., & Liu, H. (2019). Inferring user tasks in pedestrian navigation from eye movement data in real-world environments. *International Journal of Geographical Information Science*, *33*(4), 739–763. doi: 10.1080/13658816.2018.1482554

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. doi: 10.1080/15230406.2016.1174886

Lin, A. Y., Kuehl, K., Schöning, J., & Hecht, B. (2017). Understanding "Death by GPS": A Systematic Analysis of Catastrophic Incidents Associated with Personal Navigation Technologies. In *Proceedings of the 2017 chi conference on human factors in computing systems* (pp. 1154–1166). New York, NY, USA: ACM. doi: 10.1145/3025453.3025737

Lobben, A. K. (2004). Tasks, strategies, and cognitive processes associated with navigational map reading: A review perspective. *Professional Geographer*, *56*(2), 270–281. doi: 10.1111/j.0033-0124.2004.05602010.x

Lovelace, K. L., Hegarty, M., & Montello, D. R. (1999). Elements of Good Route Directions in Familiar and Unfamiliar Environments. In C. Freksa &

D. M. Mark (Eds.), *Spatial information theory. cognitive and computational foundations of geographic information science. cosit 1999. lecture notes in computer science* (Vol. 1661, pp. 65–82). Springer, Berlin, Heidelberg.

Ludwig, B., Müller, M., & Ohm, C. (2014). Empirical Evidence for Context-aware Interfaces to Pedestrian Navigation Systems. *KI - Künstliche Intelligenz*, *28*(4), 271–281. doi: 10.1007/s13218-014-0333-0

Lynch, K. (1960). *The image of the city.* Cambridge, MA: MIT Press.

Martin, F., & Ertzberger, J. (2013). Here and now mobile learning: An experimental study on the use of mobile technology. *Computers and Education*, *68*, 76–85. doi: 10.1016/j.compedu.2013.04.021

Martin, T., Kivinen, J., Rijnsdorp, J. E., Rodd, M. G., & Rouse, W. B. (1991). Appropriate Automation Integrating Technical, Human, Organizational, Economic and Cultural Factors*. *Automatica*, *27*(6), 901–917. doi: 10.1016/S1474-6670(17)52057-1

McKenzie, G., & Klippel, A. (2016). The Interaction of Landmarks and Map Alignment in You-Are-Here Maps. *The Cartographic Journal*, *53*(1), 43–54. doi: 10.1179/1743277414y.0000000101

McKinlay, R. (2016). Use or lose our navigation skills. *Nature*, *531*, 573–575. doi: 10.1038/531573a

Meilinger, T., Franz, G., & Bülthoff, H. H. (2012). From isovists via mental representations to behaviour: First steps toward closing the causal chain. *Environment and Planning B: Planning and Design*, *39*(1), 48–62. doi: 10.1068/b34048t

Meilinger, T., Hölscher, C., Büchner, S. J., & Brösamle, M. (2007). How Much Information Do You Need? Schematic Maps in Wayfinding and Self Localisation. In T. Barkowsky, M. Knauff, G. Ligozat, & D. R. Montello (Eds.), *Spatial cognition v reasoning, action, interaction. spatial cognition 2006. lecture notes in computer science* (Vol. 4387, pp. 381–400). Springer, Berlin, Heidelberg. doi: 10.1007/978-3-540-75666-8_22

Merat, N., Jamson, A. H., Lai, F. C., Daly, M., & Carsten, O. M. (2014). Transition to manual: Driver behaviour when resuming control from a highly automated vehicle. *Transportation Research Part F: Traffic Psychology and Behaviour*, *27*, 274–282. doi: 10.1016/j.trf.2014.09.005

Minaei, N. (2014). Do modes of transportation and GPS affect cognitive maps of Londoners? *Transportation Research Part A: Policy and Practice*, *70*, 162–180. doi: 10.1016/j.tra.2014.10.008

Mondschein, A., & Moga, S. T. (2018). New Directions in Cognitive-Environmental Research: Applications to Urban Planning and Design. *Journal of the American Planning Association*, *84*(3-4), 263–275. doi: 10.1080/01944363.2018.1526644

Montello, D. R. (1998). A New Framework for Understanding the Acquisition of Spatial Knowledge in Large-Scale Environments. In M. Egenhofer & R. Golledge (Eds.), *Spatial and temporal reasoning in geographic information systems* (pp. 143–154). New York: Oxford University Press.

Montello, D. R. (2005). Navigation. In P. Shah & A. Miyake (Eds.), *The cambridge handbook of visuospatial thinking* (pp. 257–294). New York, USA: Cambridge University Press.

Montello, D. R. (2009). Cognitive research in GIScience: Recent achievements and future prospects. *Geography Compass*, *3*(5), 1824–1840. doi: 10.1111/j.1749-8198.2009.00273.x

Montello, D. R., & Sas, C. (2006). Human Factors of Wayfinding in Navigation. In W. Karwowski (Ed.), *International encyclopedia of ergonomics and human factors* (2nd ed., Vol. 3, pp. 2003–2008). London: CRC Press: Taylor & Francis, Ltd. doi: 10.1201/9780849375477.ch394

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

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. doi: 10.1037/a0026553

Münzer, S., Zimmer, H. D., Schwalm, M., Baus, J., & Aslan, I. (2006). Computer-assisted navigation and the acquisition of route and survey knowledge. *Journal of Environmental Psychology*, *26*(4), 300–308. doi: 10.1016/j.jenvp.2006.08.001

Nazareth, A., Huang, X., Voyer, D., & Newcombe, N. (2019). A meta-analysis of sex differences in human navigation skills. *Psychonomic Bulletin & Review*, *26*. doi: 10.3758/s13423-019-01633-6

Norman, D. (2015). The Human Side of Automation. In G. Meyer & S. Beiker (Eds.), *Road vehicle automation 2. lecture notes in mobility* (pp. 73–79). Springer International Publishing. doi: 10.1007/978-3-319-19078-5_7

Ohm, C., Bienk, S., Kattenbeck, M., Ludwig, B., & Müller, M. (2016). Towards interfaces of mobile pedestrian navigation systems adapted to the user's orientation skills. *Pervasive and Mobile Computing*, *26*, 121–134. doi: 10.1016/j.pmcj.2015.10.006

Ohm, C., Müller, M., & Ludwig, B. (2017). Evaluating indoor pedestrian navigation interfaces using mobile eye tracking. *Spatial Cognition and Computation*, *17*(1-2), 89–120. doi: 10.1080/13875868.2016.1219913

O'Keefe, J., & Nadel, L. (1978). *The hippocampus as a cognitive map.* Oxford, UK: Oxford University Press.

O'Mara, S. (2019). *In Praise of Walking: The new science of how we walk and*

why it's good for us. London, Uk: PenguinRandomHouse.

Ooms, K., De Maeyer, P., & Fack, V. (2015). Listen to the Map User: Cognition, Memory, and Expertise. *The Cartographic Journal*, *52*(1), 3–19. doi: 10.1179/1743277413y.0000000068

Pantic, M., & Rothkrantz, L. J. (2003). Toward an affect-sensitive multimodal human-computer interaction. *Proceedings of the IEEE*, *91*(9), 1370–1390. doi: 10.1109/JPROC.2003.817122

Parasuraman, R. (2000). Designing automation for human use: Empirical studies and quantitative models. *Ergonomics*, *43*(7), 931–951. doi: 10.1080/001401300409125

Parasuraman, R., & Riley, V. (1997). Humans and Automation: Use, Misuse, Disuse, Abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *39*(2), 230–253. doi: 10.1518/001872097778543886

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A Model for Types and Levels of Human Interaction with Automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *30*(3), 286–297. doi: 10.1109/3468.844354

Parush, A., Ahuvia, S., & Erev, I. (2007). Degradation in Spatial Knowledge Acquisition When Using Automatic Navigation Systems. In S. Winter, M. Duckham, L. Kulik, & B. Kuipers (Eds.), *Spatial information theory. cosit 2007. lecture notes in computer science* (Vol. 4736, pp. 238–254). Springer, Berlin, Heidelberg. doi: 10.1007/978-3-540-74788-8_15

Pielot, M., & Rello, L. (2017). Productive, anxious, lonely - 24 Hours Without Push Notifications. In *Proceedings of the 19th international conference on human-computer interaction with mobile devices and services - mobilehci '17* (pp. 1–11). New York, USA: ACM. doi: 10.1145/3098279.3098526

Raubal, M., & Winter, S. (2002). Enriching Wayfinding Instructions with Local Landmarks. In M. Egenhofer & D. Mark (Eds.), *Geographic information science. giscience 2002. lecture notes in computer science* (Vol. 2478, pp. 243–259). Springer, Berlin, Heidelberg. doi: 10.1007/3-540-45799-2_17

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. *Quarterly Journal of Experimental Psychology*, *62*(8), 1457–1506. doi: 10.1080/17470210902816461

Richardson, A. E., Montello, D. R., & Hegarty, M. (1999). Spatial knowledge acquisition from maps and from navigation in real and virtual environments. *Memory & Cognition*, *27*(4), 741–750. doi: 10.3758/BF03211566

Richter, K.-F., Dara-Abrams, D., & Raubal, M. (2010). Navigating and learning with location based services: a user-centric design. In G. Gartner & Y. Li (Eds.), *Proceedings of the 7th international symposium on lbs and telecartography (lbs2010)* (pp. 261–276).

Richter, K.-F., Tomko, M., & Çöltekin, A. (2015). Are We There Yet? Spatial Cognitive Engineering for Situated Human-Computer Interaction. In *Cesip 2015: Cognitive engineering for spatial information processes: From user interfaces to model-driven design. workshop at the conference on spatial information theory xii (cosit 2015).* Santa Fe, NM, USA.

Richter, K.-F., & Winter, S. (2014). *Landmarks: GIScience for Intelligent Services.* Springer International Publishing.

Riehle, T., Lichter, P., & Giudice, N. (2008). An Indoor Navigation System to Support the Visually Impaired. In *30th annual international ieee embs conference.* Vancouver, British Columbia, Canada,: IEEE.

Rinner, C., Raubal, M., & Spigel, B. (2005). User interface design for location-based decision services. In *Paper presented at the 13th international conference on geoinformatics, 17-19 august 2005, proceedings (cd-rom).* Toronto, Canada.

Rodriguez Garzon, S., & Deva, B. (2014). Geofencing 2.0. In *Proceedings of the 2014 acm international joint conference on pervasive and ubiquitous computing - ubicomp '14 adjunct* (pp. 921–932). New York, USA. doi: 10.1145/2632048.2636093

Roger, M., Bonnardel, N., & Le Bigot, L. (2011). Landmarks' use in speech map navigation tasks. *Journal of Environmental Psychology*, *31*(2), 192–199. doi: 10.1016/j.jenvp.2010.12.003

Savino, G.-L., Sturdee, M., Rundé, S., Lohmeier, C., Hecht, B., Prandi, C., ... Schöning, J. (2020). Maprecorder: analysing real-world usage of mobile map applications. *Behaviour & Information Technology*, *0*(0), 1-17. doi: 10.1080/0144929X.2020.1714733

Scerbo, M. (1996). Theoretical perspectives on adaptive automation. In R. Parasuraman & M. Mouloua (Eds.), *Automation and human performance: Theory and applications* (pp. 37–63). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Schneider, G., Dreher, B., & Seidel, O. (2011). Using GeoFencing as a Means to Support Flexible Real Time Applications for Delivery Services. In *Joint proceedings of the 5th international workshop on ubiquitous computing, 4th international workshop on model-driven enterprise information systems, 3rd international workshop on technologies for context-aware business process management* (pp. 22–27). doi: 10.5220/0001737400220027

Schwarzkopf, S., Büchner, S. J., Hölscher, C., & Konieczny, L. (2017). Perspective tracking in the real world: Gaze angle analysis in a collaborative wayfinding task. *Spatial Cognition and Computation*, *17*(1-2), 143–162. doi: 10.1080/13875868.2016.1226841

Schwinger, W., Grün, C., Pröll, B., Retschitzegger, W., & Schauerhuber, A.

(2002). *Context-awareness in Mobile Tourism Guides-A Comprehensive Survey* (Tech. Rep.). Technical Report, Johannes Kepler University Linz, IFS/TK.

Sheridan, T. B. (2002). *Humans and Automation: System Design and Research Issues.* New York, NY, USA: A John Wiley & Sons, Inc., Publication.

Sheridan, T. B., & Parasuraman, R. (2005). Human-Automation Interaction. *Reviews of Human Factors and Ergonomics*, *1*, 89–129. doi: 10.1518/155723405783703082

Siegel, A. W., & White, S. H. (1975). The Development of Spatial Representations of Large-Scale Environments. In H. Reese (Ed.), *Advances in child development and behaviour* (Vol. 10, pp. 9–55). New York, USA: Academic Press.

Simpson, J., Freeth, M., Simpson, K. J., & Thwaites, K. (2018). Visual engagement with urban street edges: insights using mobile eye-tracking. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, *12*(3), 259-278. doi: 10.1080/17549175.2018.1552884

Slocum, T. A., McMaster, R. B., Kessler, F. C., & Howard, H. H. (2009). *Thematic Cartography and Geovisualization* (3rd ed.). Upper Saddle River, New Jersey, USA: Pearson Education, Inc.

Sorrows, M. E., & Hirtle, S. C. (1999). The nature of landmarks for real and electronic spaces. In C. Freksa & D. Mark (Eds.), *Spatial information theory. cognitive and computational foundations of geographic information science. cosit 1999. lecture notes in computer science* (Vol. 1661, pp. 37–50). Springer, Berlin, Heidelberg. doi: 10.1007/3-540-48384-5_3

Spiers, H. J., & Maguire, E. A. (2008). The dynamic nature of cognition during wayfinding. *Journal of Environmental Psychology*, *28*(3), 232–249. doi: 10.1016/j.jenvp.2008.02.006

Steck, S. D., & Mallot, H. A. (2000). The role of global and local landmarks in virtual environment navigation. *Presence: Teleoperators and Virtual Environments*, *9*(1), 69–83. doi: 10.1162/105474600566628

Tatler, B. W., Gilchrist, I. D., & Land, M. F. (2005). Visual memory for objects in natural scenes: From fixations to object files. *The Quarterly Journal of Experimental Psychology Section A*, *58*(5), 931–960. doi: 10.1080/02724980443000430

Taylor, H. A., Brunyé, T. T., & Taylor, S. T. (2008). Spatial Mental Representation: Implications for Navigation System Design. *Reviews of Human Factors and Ergonomics*, *4*(1), 1–40. doi: 10.1518/155723408x342835

Thorndyke, P. W., & Hayes-Roth, B. (1982). Differences in Spatial Knowledge Acquired from Maps and Navigation. *Cognitive Psychology*, *14*(4), 560–589.

Tolman, E. C. (1948). Cognitive maps in rats and men. *Psychological Review*, *55*(4), 189–208.

Trefzger, M., Blascheck, T., Raschke, M., Hausmann, S., & Schlegel, T. (2018). A visual comparison of gaze behavior from pedestrians and cyclists. In *Proceedings of the 2018 acm symposium on eye tracking research & applications - etra '18* (pp. 1–5). New York, USA: ACM Press. doi: 10.1145/3204493.3214307

Tversky, B. (1993). Cognitive maps, cognitive collages, and spatial mental models. In A. U. Frank & I. Campari (Eds.), *Spatial information theory a theoretical basis for gis. cosit 1993. lecture notes in computer science* (Vol. 716, pp. 14–24). Springer, Berlin, Heidelberg. doi: 10.1007/3-540-57207-4_2

Van Asselen, M., Fritschy, E., & Postma, A. (2006). The influence of intentional and incidental learning on acquiring spatial knowledge during navigation. *Psychological Research*, *70*(2), 151–156. doi: 10.1007/s00426-004-0199-0

Wahn, B., & König, P. (2017). Can limitations of visuospatial attention be circumvented? A review. *Frontiers in Psychology*, *8*, 1896. doi: 10.3389/fpsyg.2017.01896

Wang, R. F. (2017). Spatial updating and common misinterpretations of spatial reference frames. *Spatial Cognition and Computation*, *17*(3), 222–249. doi: 10.1080/13875868.2017.1304394

Ware, C. (2013). *Information Visualization - Perception for Design* (3rd ed.). Waltham, MA: Elsevier.

Wawrzyniak, N., & Hyla, T. (2016). Application of Geofencing Technology for the Purpose of Spatial Analyses in Inland Mobile Navigation. In *Proceedings - 2016 baltic geodetic congress (geomatics), bgc geomatics 2016* (pp. 34–39). Institute of Electrical and Electronics Engineers Inc. doi: 10.1109/BGC.Geomatics.2016.15

Webber, E., Burnett, G., & Morley, J. (2012). Pedestrian Navigation with a Mobile Device: Strategy Use and Environmental Learning. In *Proceedings of the 26th annual bcs interaction specialist group conference on people and computers* (pp. 286–291). Birmingham, UK.

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. doi: 10.1177/0963721417744521

Weiser, M. (1999). The Computer of the 21st Century. *Mobile Computing and Communications Review*, *3*(3), 3-11. doi: 10.1145/329124.329126

Weisman, J. (1981). Evaluating architectural Legibility: Way-Finding in the Built Environment. *Environment and Behavior*, *13*(2), 189–204. doi: 10.1177/0013916581132004

Wenczel, F., Hepperle, L., & von Stülpnagel, R. (2017). Gaze behavior during

incidental and intentional navigation in an outdoor environment. *Spatial Cognition and Computation*, *17*(1-2), 121–142. doi: 10.1080/13875868.2016.1226838

Wiener, J. M., Büchner, S. J., & Hölscher, C. (2009). Taxonomy of human wayfinding tasks: A knowledge-based approach. *Spatial Cognition and Computation*, *9*(2), 152–165. doi: 10.1080/13875860902906496

Willis, K. S., Hölscher, C., Wilbertz, G., & Li, C. (2009). A comparison of spatial knowledge acquisition with maps and mobile maps. *Computers, Environment and Urban Systems*, *33*(2), 100–110. doi: 10.1016/j.compenvurbsys.2009.01.004

Wolf, J., Hess, S., Bachmann, D., Lohmeyer, Q., & Meboldt, M. (2018). Automating Areas of Interest Analysis in Mobile Eye Tracking Experiments based on Machine Learning. *Journal of Eye Movement Research*, *11*(6), 6. doi: 10.3929/ethz-b-000309840

Wolter, D., & Kirsch, A. (2017). Smart Environments: What is it and Why Should We Care? *KI - Künstliche Intelligenz*, *31*(3), 231–237. doi: 10.1007/s13218-017-0498-4

Wunderlich, A., & Gramann, K. (2018). Electrocortical evidence for long-term incidental spatial learning through modified navigation instructions. In S. Creem-Regehr, J. Schöning, & A. Klippel (Eds.), *Spatial cognition xi. spatial cognition 2018. lecture notes in computer science* (Vol. 11034, pp. 261–278). Springer, Cham. doi: 10.1007/978-3-319-96385-3_18

Yates, J. J. (2017). Saving the soul of the smart city. *The Hedgehog Review: Critical Reflections on Contemporary Culture*, *19*(2), 18–35.

Zacks, J. M., & Tversky, B. (2001). Event structure in perception and conception. *Psychological Bulletin*, *127*(1), 3–21. doi: 10.1037/0033-2909.127.1.3

Zhou, J., Sun, J., Chen, F., Wang, Y., Taib, R., Khawaji, A., & Li, Z. (2015). Measurable Decision Making with GSR and Pupillary Analysis for Intelligent User Interface. *ACM Transactions on Computer-Human Interaction*, *21*(6), 1–23. doi: 10.1145/2687924

APPENDIX A

PUBLICATIONS RELATED TO Ph.D.

Articles and conference contributions

Thrash, T., Lanini-Maggi, S., Fabrikant, S.I., **Brügger A.**, Credé, S., Richter, K.-F., Do, C.T., Huang, H., Münzer, S., Garnter G., & Bertel, S. (2019) The Future of Geographic Information Displays from GIScience, Cartographic, and Cognitive Science Perspectives, (Vision Paper). In proceedings of the 14th international conference on spatial information theory - COSIT2019. Dagstuhl, Germany. DOI:10.4230/LIPIcs.COSIT.2019.19

Brügger, A., Richter, K.-F. & Fabrikant, S.I. (2019) How does navigation system behavior influence human behavior? Cognitive Research: Principles and Implications, 4:5. DOI: 10.1186/s41235-019-0156-5.
→ *Award for Best Paper of the Year for Cognitive Research: Principles and Implications.*

Brügger, A., Richter, K.-F. & Fabrikant, S.I. (2018a) Space-time segmentation of sensor data along a route. Spatial Cognition 2018, Tübingen, DE.

Brügger, A., Richter, K.-F. & Fabrikant, S.I. (2018b) Which egocentric direction suffers from visual attention during aided wayfinding? Proceedings of the 3rd International Workshop on Eye Tracking for Spatial Research (ET4S), Kiefer P. , Giannopoulos I., Göbel F., Raubal M., Duchowski A. (Eds), LBS2018, Zurich, CH. DOI: 10.3929/ethz-b-000222472

Brügger, A., Richter, K.-F. & Fabrikant, S.I. (2017a) Distributing attention between environment and navigation system to increase spatial knowledge acquisition during assisted wayfinding. Short-peer reviewed paper proceedings of COSIT 2017, l'Aquila, ITA. DOI:10.1007/978-3-319-63946-8
→ *Award for Best Poster Presentation*

Brügger, A., Fabrikant, S.I. & Richter, K.-F. (2017b) Balancing human engagement and device assistance. Urban Wayfinding and the Brain 2017, London, UK.

Brügger, A. (2017a) Balancing Human Engagement and Device Assistance to Ensure Navigation Efficiency and Spatial Knowledge Acquisition. Doctoral colloquium, COSIT 2017, l'Aquila, ITA.

Brügger, A. (2017b) Conference Report GIScience 2016 in the special issue on "Landmark-Based Navigation in Cognitive Systems" for Springer's German Journal on Artificial Intelligence. DOI: 10.1007/s13218-017-0490-z

Brügger, A., Richter, K.-F. & Fabrikant, S.I. (2016) Walk and Learn: An Empirical Framework for Assessing Spatial Knowledge Acquisition during Mobile Map Use. Short-peer reviewed paper proceedings of GIScience 2016, Montreal, CAN. DOI: 10.21433/B3113hc8k3js
→ *Award for Best Short-Peer Reviewed Paper*

Media communications

So behalten wir trotz Google Maps unsere Raumvorstellung (2019), Higgs.
https://www.higgs.ch/
so-behalten-wir-trotz-google-maps-unsere-raumvorstellung/18590/

Training fürs "Bio-Navi" (2018), TV contribution on 3sat Nano.
http://www.3sat.de/mediathek/?mode=&obj=77292

Digitale Pfadfinder (2017), UZH Magazin.
https://www.magazin.uzh.ch/dam/jcr:
565a0548-0d19-46bd-83f4-65c5a628a7ca/UZH-Magazin_4-17_16.pdf

Emotive (2017), Video for Digital Society Initiative UZH.
https://www.dsi.uzh.ch/de/research/projects/emotive.html

APPENDIX B

EXPERIMENT 1

B.1 Demographics questionnaire

Personalien

* User ID

* Geschlecht

- weiblich
- männlich

* Alter

* Wurde Ihnen von einer professionellen Fachperson (Optiker, Augenarzt) schon einmal gesagt, dass Sie eine Sehschwäche (z.B. Brille/Kontaktlinsen, Farbenblindheit) haben?

- Nein
- Ja, ich trage eine Brille/Kontaktlinsen.
- Ja, ich bin farbenblind.
- Ja. Andere:

* Benutzen Sie privat eines der folgenden mobilen Geräten?

- Smartphone
- Tablet
- GPS-Navigationsgerät
- Ich besitze kein solches Gerät.
- Ja. Andere:

* Wie oft benutzen Sie Karten-Apps auf Ihren mobilen Geräten?

- ◯ Sehr häufig (mind. 1 Mal pro Tag)
- ◯ Häufig (3-4 Mal pro Woche)
- ◯ Gelegentlich (2-3 Map pro Monat)
- ◯ Selten (2-3 Mal pro Halbjahr)
- ◯ Nie

* Wie gross ist Ihre Erfahrung in folgenden Bereichen?

	1 (keine Erfahrung)	2	3	4	5 (täglicher Gebrauch / professionell)
Karten lesen	◯	◯	◯	◯	◯
Benutzung von Karten-Apps für die Navigation und Routenplanung	◯	◯	◯	◯	◯
Kartographie	◯	◯	◯	◯	◯
Geografische Informationssysteme (GIS)	◯	◯	◯	◯	◯
Sportart "Orientierungslauf"	◯	◯	◯	◯	◯

* Wie gut kennen Sie das Stadtquartier Oerlikon in Zürich?

- ◯ Sehr gut
- ◯ Gut
- ◯ Nur wenig
- ◯ Schlecht
- ◯ Gar nicht

B.2 Post questionnaire

Fragen zum Experiment

* 1. User ID

* 2. Gruppennummer

- 1
- 2
- 3
- 4

Hinweg

* 3. "Die GPS-Positionsanzeige hat mir bei der Navigation auf dem Hinweg geholfen um mich zu orientieren." Diese Aussage trifft....

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

* 4. Mussten Sie die Textinformation selber eingeben?

- Ja.
- Nein.

Andere Eingaben

* 5. "Ich würde im Nachhinein...

	überhaupt nicht zu.		teilweise zu.		stark zu.
...andere Positionen für meine Textinformationen wählen." Diese Aussage trifft....	○	○	○	○	○
...andere Textinformation an den gewählten Positionen eingeben." Diese Aussage trifft....	○	○	○	○	○

Welche andere Positionen / Informationen?

Andere Informationen

* 6. "Nachdem ich das Experiment gemacht habe, würde ich andere ...

	überhaupt nicht zu.		teilweise zu.		stark zu.
...Textinformationen (inhaltlich) bevorzugen." Diese Aussage trifft...	○	○	○	○	○
...andere Positionen bevorzugen." Diese Aussage trifft....	○	○	○	○	○

Wenn andere Information. Welcher Art?

Umgebungswahrnehmung

* 7. "Die mobile Karte hat mich auf dem Hinweg von der Wahrnehmung der Umgebung abgelenkt". Diese Aussage trifft...

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

Was genau hat Sie abgelenkt?

* 8. "Die mobile Karte hat mich animiert, mich mehr auf die Umgebung zu konzentrieren. " Diese Aussage trifft...

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

* 9. "Die Eye-tracking Brille hat mich von der Wahrnehmung der Umgebung abgelenkt". Diese Aussage trifft...

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

Rückweg

* 10. Wie schwierig war für Sie die Aufgabe "Laufen Sie dieselbe Route ohne Navigationshilfe zurück"?

- ○ Sehr schwierig
- ○ Schwierig
- ○ Neutral
- ○ Einfach
- ○ Sehr einfach

11. Was genau hat Ihnen bei dieser Aufgabe am meisten Schwierigkeiten bereitet?

[ ]

* 12. "Ich habe die Umgebung auf dem Rückweg wieder erkannt." Diese Aussage trifft...

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

* 13. "Die Textinformation hat mir geholfen den Rückweg wieder zu finden." Diese Aussage trifft....

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

* 14. "Die Textinformationen haben mir geholfen, die Orientierungspunkte auf dem Rückweg wieder zu erkennen." Diese Aussage trifft....

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

* 15. "Ich konnte mich noch an alle 3 Textinformationen (inhaltlich) erinnern." Diese Aussage trifft....

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

* 16. "Ich konnte mich noch an alle 3 Positionen der Textinformationen erinnern." Diese Aussage trifft....

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

Applikation etc.

* 17. "Im Nachhinein würde ich meine Nutzung des mobilen Gerätes beim Hinweg ändern." Diese Aussage trifft...

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

Was genau würden Sie an der Nutzung ändern?

* 18. "Die mobile Kartenapplikation war einfach zu verstehen/bedienen." Diese Aussage trifft...

überhaupt nicht zu.		teilweise zu.		stark zu.
○	○	○	○	○

* 19. Was sollte man Ihrer Meinung nach an der mobilen Kartenapplikation ändern? Was hat Ihnen gefehlt, damit Sie die Aufgabe noch besser hätten lösen können?

20. Allgemeine Kommentare zum Experiment:

21. Ihnen wird nun eine Karte auf Papier gegeben. Bitte lösen Sie diese Aufgabe direkt auf dem Papier.

Vielen Dank für Ihre Angaben!

B.3 Text of automatic markers for groups AllocSys_

In Experiment 1, two groups received three times a sentence (by the system) referring to a landmark in the environment (Level 9 of the cognitive process 'allocation of attention'). The three sentences are:

- Dieses von Pflanzen überwachsene Haus ist ein Pflegeheim. (English translation: This house overgrown with plants is a nursing home.)
- Fahnenmasten sind typisch für viele Schweizer Gärten. (English translation: Flagpoles are typical for many Swiss gardens.)
- Der Bus Nr. 75 verbindet die Quartiere Seebach & Schwamendingen. (English translation: The bus no. 75 connects the districts Seebach & Schwamendingen.)

B.4 Scenarios and tasks for both phases of the empirical framework

Scenario and task Phase 1 for group AllocHum_LocHum:

Stellen Sie sich vor, Sie besuchen einen alten Bekannten, der gerade in eine andere Stadt gezogen ist. Sie sind an der aktuellen Stelle aus dem Bus gestiegen. Sie haben nun im Navigationsplaner Ihren aktuellen Standort und Ihren Zielpunkt (Haus Ihres Bekannten) eingegeben. Die Route dorthin wird Ihnen automatisch berechnet und angezeigt. Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Ihre aktuelle Position können Sie sich jederzeit mittels GPS-Knopf anzeigen lassen. Die Anzeige verschwindet nach ca. 10 sec wieder. Auf dem Weg zu Ihrem Bekannten sollten Sie sich drei Orte notieren (Stichworte mittels Marker-Button), welche für Sie für diese Route relevant/spannend sind. Die Position an welchem dieser Eintrag erfolgt wird mit der Textinformation zusammen abgespeichert und später in die Applikation eingebaut. Der Eintrag erfolgt jeweils an der Stelle an der Sie den Marker-Button

klicken. Wie bereits im Testlauf gesehen, zeigt die Zahl neben dem Button Ihnen die verbleibende zu setzende Anzahl Marker an.

Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Sobald Sie das Ziel erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die Route möglichst schnell (jedoch ohne zu rennen) und ohne Fehler ablaufen. Verwenden Sie die mobile Karte als Navigationshilfe.

Scenario and task Phase 1 for group AllocHum_LocSys:

Stellen Sie sich vor, Sie besuchen einen alten Bekannten, der gerade in eine andere Stadt gezogen ist. Sie sind an der aktuellen Stelle aus dem Bus gestiegen. Sie haben nun im Navigationsplaner Ihren aktuellen Standort und Ihren Zielpunkt (Haus Ihres Bekannten) eingegeben. Die Route dorthin wird Ihnen automatisch berechnet und angezeigt. Ihre aktuelle Position wir Ihnen jederzeit mittels blauem GPS-Punkt auf der Karte angezeigt. Auf dem Weg zu Ihrem Bekannten sollten Sie sich drei Orte notieren (Stichworte mittels Marker-Button), welche für Sie für diese Route relevant/spannend sind. Die Position an welchem dieser Eintrag erfolgt wird mit der Textinformation zusammen abgespeichert und später in die Applikation eingebaut. Der Eintrag erfolgt jeweils an der Stelle an der Sie den Marker-Button klicken. Wie bereits im Testlauf gesehen, zeigt die Zahl neben dem Button Ihnen die verbleibende zu setzende Anzahl Marker an.

Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Sobald Sie das Ziel erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die Route möglichst schnell (jedoch ohne zu rennen) und ohne Fehler ablaufen. Verwenden Sie die mobile Karte als Navigationshilfe.

Scenario and task Phase 1 for group AllocSys_LocHum:

Stellen Sie sich vor, Sie besuchen einen alten Bekannten, der gerade in eine andere Stadt gezogen ist. Sie sind an der aktuellen Stelle aus dem Bus gestiegen. Sie haben nun im Navigationsplaner Ihren aktuellen Standort und Ihren Zielpunkt (Haus Ihres Bekannten) eingegeben. Die Route dorthin wird Ihnen automatisch berechnet und angezeigt. Ihre aktuelle Position können Sie sich

jederzeit mittels GPS-Knopf anzeigen lassen. Die Anzeige verschwindet nach ca. 10 sec wieder. Zudem werden Ihnen auf dem Weg zu Ihrem Bekannten an gewissen (relevanten/spannenden) Positionen routenspezifische Informationen auf der Karte angezeigt. Wie bereits im Testlauf gesehen sollte diese Information wieder verschwinden sobald Sie sich von dem Ort entfernen.

Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Sobald Sie das Ziel erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die Route möglichst schnell (jedoch ohne zu rennen) und ohne Fehler ablaufen. Verwenden Sie die mobile Karte als Navigationshilfe.

Scenario and task Phase 1 for group AllocSys_LocSys:

Stellen Sie sich vor, Sie besuchen einen alten Bekannten, der gerade in eine andere Stadt gezogen ist. Sie sind an der aktuellen Stelle aus dem Bus gestiegen. Sie haben nun im Navigationsplaner Ihren aktuellen Standort und Ihren Zielpunkt (Haus Ihres Bekannten) eingegeben. Die Route dorthin wird Ihnen automatisch berechnet und angezeigt. Ihre aktuelle Position wird Ihnen jederzeit mittels blauem GPS-Punkt auf der Karte angezeigt. Zudem werden Ihnen auf dem Weg zu Ihrem Bekannten an gewissen (relevanten/spannenden) Positionen routenspezifische Informationen auf der Karte angezeigt. Wie bereits im Testlauf gesehen sollte diese Information wieder verschwinden sobald Sie sich von dem Ort entfernen.

Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Wenn Sie das Ziel erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die Route möglichst schnell (jedoch ohne zu rennen) und ohne Fehler ablaufen. Verwenden Sie die mobile Karte als Navigationshilfe.

Scenario and task Phase 2 for all groups:

Sie sind am Ziel angelangt. Sie stellen jedoch fest, dass Sie unterwegs Ihre Schlüssel verloren haben und müssen daher die genau gleiche Strecke nochmals ablaufen. Leider funktioniert das Navigationsgerät nicht mehr und Sie müssen die Route ohne Hilfe wieder finden. Sobald Sie den ursprünglichen Startpunkt

erreicht haben, geben Sie der Experimentleiterin ein deutliches Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die genau gleiche Route (ohne Abkürzungen) möglichst schnell (jedoch ohne zu rennen) und ohne Fehler zurücklaufen. Sollten Sie einen Fehler machen, wird die Experimentleiterin Sie wieder zurück auf den richtigen Weg bringen. Ihnen stehen für diese Aufgabe keine Hilfsmittel zur Verfügung.

B.5 Keywords for self-selected markers

Own Markers by two groups "AllocHum_ "

original keywords in German (A-Z)	keywords translated to English
Abfallsammelstelle	disposal of waste
alterspflegeheim	residential home
altglas	disposal of waste
apartementhouse victoria	building viktoria
apartmenthouse viktoria	building viktoria
apartmenthouse viktoria	building viktoria
blindenstreifen auf gehsteig	white blind lines on pavement
bushaltestelle	bus stop
bushaltestelle	bus stop
bushaltestelle	bus stop
bushaltestelle	bus stop friedackerstrasse
bushaltestelle friedackerstrasse	bus stop
bushaltestelle friedackerstrasse	bus stop friedackerstrasse
bushaltestelle friedackerstrasse	bus stop friedackerstrasse
Bushaltestelle Friedackerstrasse	bus stop friedackerstrasse
bushaltestelle friedackerstrasse	bus stop friedackerstrasse
Bushaltestelle vor Kirchengebäude	bus stop
bushaltestelle, nb: die weissen blindenlinien hier verwirren	bus stop: (comment: the white blind lines are confusing)
Container	disposal of waste
ende 30er zone	End 30km zone
ende parkhecke	end park hedge corner 1
ende parkhecke 2	end park hedge corner 2
Entsorgungsstelle	disposal of waste
entsorgungsstelle	disposal of waste
Entsorgungsstelle (Glas, Papier, ...)	disposal of waste
Fahnenmasten	flag staff
frau mit hund	woman with dog
Friedhof Oerlikon	cemetary oerlikon
friedhof, park	cemetary, park
gebädeform und position	form of building and position
gefällter Baum	felt tree
Glasentsorgestelle	disposal of waste
glassammelstelle	disposal of waste
gosse kreuzung, 2 strassenschilder, 2 männer, blätter am boden	bis intersection, 2 street signs, 2 men, leaves on the floor
grünanlage, bushaltestelle	green space, bus stop
grosse Grube	hole in the ground
grosser Baum beim schild Rösslerweg	big tree with street-sign R„sslerweg
grosser turmspitz	steepletop
grosses helles einfamilienhaus	big bright one-family house
H Pflegeheim	residential home
haupteingang friedhof oerlikon	main entrance cemetary oerlikon
haus mit efeu	house with ivy
haus mit rotem Balkongelaender	house with red balcony bannister
haus mit roten blätter	house with red leaves
Haus mit Türmchen	house with turret
hydrant	hydrant
katze, wegschild, gelbe blätter/bäume	cat, street sign, yellow leaves/trees
kein vortritt schild	give way sign
kirche	church
kirche	church
kirche	church

Kirche	church
kirche	church
Kirche Herz-Jesu Oerlikon	church
kirche in blickrichtung auf der linken seite	church
Kirche Oerlikon	church
Komplett überwachsenes Haus	completly overgrown house
kreuzung mit 4 bäumen und 2 fahnenstangen	intersection with 4 trees and 2 flag staffs
kreuzung mit schraffierten eingängen	intersection with hatched entrances
kreuzung mitgewelltem eingang, bushaltestelle und grünen ecken	intersection with wavy entrance, bus stop and green corners
kreuzung parkecke	intersection park
leute steigen in auto	people getting in a car
loch in der erde	hole in the ground
mir gut bekannte schwamendingrrstrasse	schwamendingerstrasse
muellcontainwr	disposal of waste
neubau orange weiss	New building with colours orange and white
park	park
park	park
pflegeheim	residential home
pflegeheim	residential home
pflegeheim	residential home
pflegeheim rechts	residential home
pflegeheim schild	sign residential home
pflegezentrum	residential home
pfleggeheim schilf fuer parkplatz	sign residential home
recyclingstelle	disposal of waste
ROTER Hydrant	red hydrant
rotes auto	red car
rotes Laub/blätter	red folliage, leaves
sammelstelle	disposal of waste
schild viktoriastr.	street sign viktoriastrasse
schönes alleinstehendes Haus	beautiful one-family house
schuld pflegeheim rote blätter	residential home, red leaves
Schweiz. Blindenbund	swiss blind dog house
spiegel	mirror
strasse herunter	down the street
strassenname, tafel	street name, sign
Tafel Pflegeheim	residential home sign
turmspitze	steepletop
über fussgängerstreiffen	pedestrian crossing
versetzte kreuzung, müll	shiftet intersection, disposal of waste
viktoria apartmenthaus	building viktoria
Vor Kirche rechts in 30er zone	turn right in zone 30km before church
wenn ich geradeaus weiter der strasse folgen wuerde kommt ein einfahrtsverbotsschild, mit dem auto koennte ich also gar nicht weiter geradeaus sondern nur links fahren	straight ahead sign no entry, can only go left as a car driver
werkstoffsammelstelle	disposal of waste

B.6 Descriptive statistics

The tables report the mean (M) and standard deviation (SD) of questionnaires and measurements across groups.

Scale	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
Total	M=4.28 SD=1.42	M=4.43 SD=1.08	M=3.81 SD=1.27	M=4.02 SD=0.86
Global-egocentric orientation	M=4.22 SD=1.49	M=4.30 SD=1.02	M=3.76 SD=1.13	M=3.95 SD=0.87
Survey	M=4.44 SD=1.36	M=4.64 SD=1.19	M=4.05 SD=1.50	M=4.27 SD=1.04
Cardinal direction	M=4.03 SD=1.47	M=4.34 SD=1.53	M=3.18 SD=1.43	M=3.53 SD=1.16
Question 12	M=4.62 SD=1.89	M=5.12 SD=1.31	M=4.18 SD=1.97	M=5.06 SD=1.34

Table B.1: Self-assessment questionnaire Räumliche Strategie (Münzer & Hölscher, 2011). Strategic scale: total (questions 1-19), global-egocentric orientation (questions 1-10), survey (questions 11-17), cardinal direction (questions 18-19), and the specific question 12: "I am good in remembering routes and finding my way back without problems"

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
Score	M=21.07 SD=2.64	M=20.61 SD=3.17	M=20.42 SD=3.71	M=18.98 SD=5.02

Table B.2: Building Memory test (Ekstrom et al., 1976). The higher the score, the more buildings were correctly located. Zero points: all buildings were placed at wrong locations. 24 points: all buildings were correctly positioned.

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
Phase 1	M=9.13 SD=0.89	M=9.19 SD=1.17	M=9.06 SD=1.00	M=9.69 SD=1.25
Phase 2	M=8.31 SD=1.08	M=8.19 SD=0.91	M=8.34 SD=1.15	M=8.38 SD=1.59

Table B.3: Navigation efficiency. Route completion times for Phase 1 and Phase 2 across groups.

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
Stops Phase 1	M=2.25 SD=1.61	M=2.25 SD=0.93	M=0.44 SD=0.63	M=0.69 SD=1.01
Stops Phase 2	M=0.13 SD=0.34	M=0.19 SD=0.40	M=0.56 SD=0.895	M=0.38 SD=0.62
Hesitations Phase 1	M=0.75 SD=0.86	M=0.06 SD=0.25	M=0.31 SD=0.60	M=0.31 SD=0.87
Hesitations Phase 2	M=0.5 SD=0.63	M=0.44 SD=0.51	M=1.31 SD=1.19	M=1.06 SD=1.61

Table B.4: Stops and hesitations. Stops and hesitations for Phase 1 and Phase 2 across groups.

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
AllocHum _LocHum	-	-	-	-
AllocHum _LocSys	2.750 (15.78*)	-	-	-
AllocSys _LocHum	23.000**	25.750***	-	-
AllocSys _LocSys	19.875*	22.625**	3.125	-

Table B.5: Pairwise comparisons for stops and hesitations (in brackets) during Phase 1 across groups. Critical difference at value 17.36714. P value adjustment method 'Bonferroni': *p<.05,**p<.01,***p<.001.

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
Map interactions	M=54.50 SD=37.39	M=19.75 SD=14.98	M=45.50 SD=21.28	M=21.50 SD=26.24

Table B.6: Map interactions. Counts of interactions with the map display during Phase 1 across groups.

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
AllocHum _LocHum	-	-	-	-
AllocHum _LocSys	19.75000*	-	-	-
AllocSys _LocHum	1.34375	18.40625**	-	-
AllocSys _LocSys	21.15625*	1.40625	19.81250*	-

Table B.7: Pairwise comparisons for map interactions during Phase 1 across groups. Critical difference at value 17.36714. P value adjustment method 'Bonferroni': *p<.05,**p<.01.

	AllocHum _LocHum	AllocSys _LocHum
Count	M=4.61 SD=4.89	M=11.46 SD=7.37
Percentage of time	M=12.43 SD=12.86	M=30.725 SD=18.27

Table B.8: Use of 'GPS on' button. Counts of pressing the 'GPS on' button and percentage of total time that self-localization is displayed.

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
Before Phase 2	M=2.43 SD=1.15	M=2.37 SD=1.14	M=2.97 SD=0.92	M=2.81 SD=0.75
After Phase 2	M=2.12 SD=0.80	M=2.12 SD=0.95	M=2.43 SD=0.15	M=2.31 SD=1.07

Table B.9: Rating of task difficulty. Rating scale: 1 (very easy) to 5 (very difficult). Rating the difficulty of Phase 2 at different stages (before and after) across groups.

	AllocHum _LocHum	AllocHum _LocSys	AllocSys _LocHum	AllocSys _LocSys
Errors	M=0.25 SD=0.58	M=0.31 SD=0.70	M=1 SD=1.03	M=0.69 SD=1.08

Table B.10: Navigation errors. Number of navigation errors at intersections during Phase 2 across groups.

APPENDIX C

EXPERIMENT 2

C.1 Demographics questionnaire

Navigation-Studie GEO UZH: Personalien

Vielen Dank für Ihr Interesse und Ihre Teilnahme an der Studie. Bitte füllen Sie folgende Fragen aus und klicken Sie am Schluss auf den "Fragebogen beenden und abschicken" Knopf, damit Ihre Angaben gespeichert werden.

UserID *

Alter *

123

Geschlecht *

- weiblich
- männlich
- anderes

Wurde Ihnen von einer professionellen Fachperson (Optiker, Augenarzt) schon einmal gesagt, dass Sie eine Sehschwäche (z.B. Kurzsichtigkeit, Farbenblindheit) haben? *

- [ ] Nein
- [ ] Ja, ich trage eine Brille/Kontaktlinsen.
- [ ] Ja, ich bin farbenblind.
- [ ] anderes

Benutzen Sie privat eines der folgenden mobilen/digitalen Geräten? *

- [ ] Smartphone
- [ ] Tablet
- [ ] GPS-Navigationsgerät
- [ ] Ich besitze kein solches Gerät.
- [ ] Andere

Wie oft benutzen Sie Karten-Apps auf Ihren mobilen/digitalen Geräten? *

sehr häufig (mind. 1 mal pro Tag)	Häufig (3-4 Map pro Woche)	Gelegentlich (2-3 Mal pro Monat)	Selten (2-3 Mal pro Halbjahr)	Nie
○	○	○	○	○

Wie gross ist Ihre Erfahrung in folgenden Bereichen?

	1 (keine Erfahrung)				täglicher Gebrauch/professionell
Karten lesen *	○	○	○	○	○
Benutzung von Karten-Apps *	○	○	○	○	○
Kartographie *	○	○	○	○	○
Geographische Informationssysteme (GIS) *	○	○	○	○	○
Sportart "Orientierungslauf" *	○	○	○	○	○

Wie gut kennen Sie die folgenden Stadtquartiere von Zürich?

	sehr gut	gut	nur wenig	schlecht	gar nicht
Enge *	○	○	○	○	○
Langstrasse *	○	○	○	○	○
Alt-Wiedikon *	○	○	○	○	○
Werd *	○	○	○	○	○

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C.2 Post questionnaire

Navigation-Studie2 GEO UZH: Postquestionnaire

UserID *

Wie schätzen Sie die Navigationsaufgabe (den genau gleichen Weg zurückzufinden) ein? *

○ sehr schwierig ○ schwierig ○ neutral ○ einfach ○ sehr einfach

"Die GPS-Positionsanzeige hat mir bei der Navigation auf dem Hinweg geholfen um mich zu orientieren und zu lokalisieren." Diese Aussage trifft… *

○ überhaupt nicht zu ○ ○ teilweise zu ○ ○ stark zu

„Die digitale Karte hat mich auf dem Hinweg motiviert die Umgebung wahrzunehmen." Diese Aussage trifft…. *

○ überhaupt nicht zu ○ ○ teilweise zu ○ ○ stark zu

„Die Eye-tracking Brille hat mich von der Wahrnehmung der Umgebung abgelenkt." Diese Aussage trifft… *

○ überhaupt nicht zu ○ ○ teilweise zu ○ ○ stark zu

Bewerten Sie folgende Aussagen: Wie sehr haben Ihnen die folgenden Faktoren geholfen, den Rückweg wieder zu finden?

	überhaupt nicht				sehr stark
Digitale Karte *	○	○	○	○	○
Struktur der Route (z.B. Segmente, Abbiegungen) *	○	○	○	○	○
Umgebungselemente / Landmarken *	○	○	○	○	○

Hat Ihnen noch ein anderer Faktor geholfen, den Rückweg zu finden? Wenn ja, welcher?

1000

Powered by Survey123 for ArcGIS

C.3 Scenarios and tasks for both phases of the empirical framework

Scenario and task Phase 1 for group LocHum_sr:

Stellen Sie sich vor, Sie besuchen einen alten Bekannten, der gerade in eine andere Stadt gezogen ist. Sie sind an der aktuellen Stelle aus dem Taxi/Bus gestiegen. Sie haben nun im Navigationsplaner Ihren aktuellen Standort (blauer Pin) und Ihren Zielpunkt (Haus Ihres Bekannten/Flagge) eingegeben. Die Route dorthin wird Ihnen automatisch berechnet und angezeigt. Ihre aktuelle Position können Sie sich jeweils an einer Kreuzung mittels GPS-Knopf auf der Karte anzeigen lassen. Sie können die Karte ganz nach Ihrem Bedürfnis nutzen (Zoom, Rotation, etc.).

Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Wenn Sie denken, dass Sie das Ziel erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die Route möglichst schnell (jedoch ohne zu rennen) und ohne Fehler ablaufen. Verwenden Sie die digitale Karte als Navigationshilfe.

Scenario and task Phase 1 for group LocSys_sr:

Stellen Sie sich vor, Sie besuchen einen alten Bekannten, der gerade in eine andere Stadt gezogen ist. Sie sind an der aktuellen Stelle aus dem Taxi/Bus gestiegen. Sie haben nun im Navigationsplaner Ihren aktuellen Standort (blauer Pin) und Ihren Zielpunkt (Haus Ihres Bekannten/Flagge) eingegeben. Die Route dorthin wird Ihnen automatisch berechnet und angezeigt. Ihre aktuelle Position wird Ihnen jeweils an einer Kreuzung mittels blauem GPS-Punkt auf der Karte angezeigt. Sie können die Karte ganz nach Ihrem Bedürfnis nutzen (Zoom, Rotation, etc.).

Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Wenn Sie denken, dass Sie das Ziel erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die Route möglichst schnell (jedoch ohne zu rennen) und ohne Fehler ablaufen. Verwenden Sie die digitale Karte als Navigationshilfe.

Scenario and task Phase 1 for group LocSys:

Stellen Sie sich vor, Sie besuchen einen alten Bekannten, der gerade in eine andere Stadt gezogen ist. Sie sind an der aktuellen Stelle aus dem Taxi/Bus gestiegen. Sie haben nun im Navigationsplaner Ihren aktuellen Standort (blauer Pin) und Ihren Zielpunkt (Haus Ihres Bekannten/Flagge) eingegeben. Die Route dorthin wird Ihnen automatisch berechnet und angezeigt. Ihre aktuelle Position haben Sie jederzeit mittels blauem GPS-Punkt auf der Karte angezeigt. Sie können die Karte ganz nach Ihrem Bedürfnis nutzen (Zoom, Rotation, etc.).

Folgen Sie nun der markierten Route, bis Sie das Ziel erreicht haben. Wenn Sie denken, dass Sie das Ziel erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die Route möglichst schnell (jedoch ohne zu rennen) und ohne Fehler ablaufen. Verwenden Sie die digitale Karte als Navigationshilfe.

Scenario and task Phase 2 for all groups:

Sie sind am Ziel angelangt. Sie stellen jedoch fest, dass Sie unterwegs Ihren Schlüsselbund verloren haben und müssen daher die genau gleiche Strecke wieder zurück laufen um den Schlüsselbund zu finden. Leider funktioniert das Navigationsgerät nicht mehr und Sie müssen die Route ohne Hilfe wieder finden. Sobald Sie den ursprünglichen Startpunkt erreicht haben, geben Sie der Experimentleiterin ein Zeichen, indem Sie die Hand hochhalten.

Ziel: Sie sollten die genau gleiche Route (ohne Abkürzungen) möglichst schnell (jedoch ohne zu rennen) und ohne Fehler bis zum ursprünglichen Startpunkt zurückzulaufen. Ihnen stehen für diese Aufgabe keine Hilfsmittel zur Verfügung. Falls Sie an einer Kreuzung falsch abbiegen, wird die Experimentleiterin Sie an die Kreuzung zurückrufen. Somit haben Sie die Möglichkeit sich nochmals neu zu entscheiden.

C.4 Descriptive statistics

The tables report the mean (M) and standard deviation (SD) of questionnaires and measurements across groups.

Scale	LocHum _sr	LocSys _sr	LocSys
Total	M=4.40 SD=1.08	M=4.10 SD=0.43	M=3.86 SD=1.11
Global-egocentric orientation	M=4.29 SD=1.15	M=3.94 SD=0.53	M=3.68 SD=0.99
Survey	M=4.66 SD=0.97	M=4.28 SD=0.75	M=4.12 SD=1.33
Cardinal direction	M=4.04 SD=1.66	M=4.25 SD=0.80	M=3.80 SD=1.33
Question 12	M=5.36 SD=1.01	M=4.57 SD=1.09	M=4.2 SD=1.61

Table C.1: Self-assessment questionnaire Räumliche Strategie (Münzer & Hölscher, 2011). Strategic scale: total (questions 1-19), global-egocentric orientation (questions 1-10), survey (questions 11-17), cardinal direction (questions 18-19), and the specific question 12:"I am good in remembering routes and finding my way back without problems"

	LocHum _sr	LocSys _sr	LocSys
Phase 1	M=10.25 SD=1.64	M=10.23 SD=1.20	M=9.99 SD=0.77
Phase 2	M=10.01 SD=0.75	M=11.10 SD=1.69	M=10.28 SD=1.12

Table C.2: Navigation efficiency. Route completion times for Phase 1 and Phase 2 across groups.

	LocHum _sr	LocSys _sr	LocSys
Stops Phase 1	M=1.23 SD=1.59	M=0.71 SD=0.83	M=0.71 SD=1.20
Stops Phase 2	M=0.77 SD=1.175	M=0.79 SD=0.97	M=0.71 SD=0.91
Hesitations Phase 1	M=0.31 SD=0.63	M=0.71 SD=0.91	M=0.64 SD=1.15
Hesitations Phase 2	M=0.85 SD=0.80	M=2.07 SD=1.54	M=1.36 SD=1.34

Table C.3: Stops and hesitations. Stops and hesitations for Phase 1 and Phase 2 across groups.

	LocHum _sr
Count	M=2.14 SD=2.14
Percentage of time	M=3.51 SD=3.55

Table C.4: Use of 'GPS on' button. Counts of pressing the 'GPS on' button and percentage of total time that self-localization is displayed.

	LocHum _sr	LocSys _sr	LocSys
Map interactions	M=85.50 SD=53.56	M=80.85 SD=50.41	M=65.23 SD=44.64

Table C.5: Map interactions. Counts of interactions with the map display during Phase 1 across groups.

	LocHum _sr	LocSys _sr	LocSys
Before Phase 2	M=3.00 SD=0.96	M=3.14 SD=0.95	M=3.40 SD=0.83
After Phase 2	M=3.21 SD=1.19	M=2.93 SD=1.14	M=3.13 SD=0.99

Table C.6: Rating of task difficulty. Rating scale: 1 (very easy) to 5 (very difficult). Rating the difficulty of Phase 2 at different stages (before and after) across groups.

	LocHum _sr	LocSys _sr	LocSys
Errors	M=1.50 SD=1.45	M=1.43 SD=1.55	M=1.87 SD=1.55

Table C.7: Navigation errors. Number of navigation errors at intersections during Phase 2 across groups.

APPENDIX D

CURRICULUM VITAE

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born November, 2nd 1987, in Solothurn SO (CH) from Plaffeien FR (CH)

Education

2015 - 2020: **Ph.D.**, University of Zurich, Department of Geography, Geographic Information Visualization & Analysis

- Thesis: "Walk and Learn: Effects of Human-Centered Navigation Systems on Pedestrians' Navigation Behavior"

2012 - 2015: **Master of Science** in Geography, University of Zurich

- Thesis: "Where are the Ups and Downs? Evaluating Elevation Representations for Bicycle Paths in City Maps"
- Minor: Cartography (ETH Zurich) and Atmosphere & Climate (ETH Zurich)

2009 - 2012: **Bachelor of Science** in Geography, University of Zurich

- Thesis: "Remote Sensing of Vegetation Dynamics in the Sahel Region"

2002 - 2007: **Matura**, Kantonsschule Solothurn

- Major: Applied Mathematics & Physics