University of Zurich[UZH]

Pedestrian Route-Following Performance Under the Influence of Stress in a Virtual Urban Environment

GEO 620 Master's Thesis

Author
Matthias Saner
12-722-096

Supervised by
Prof. Dr. Sara Irina Fabrikant

Faculty representative
Prof. Dr. Sara Irina Fabrikant

30.04.2021
Department of Geography, University of Zurich

ABSTRACT

Nowadays, most of us rely on an online mapping service to find the most efficient route to a specific destination when visiting an unfamiliar city. Based on our current location, a navigational assistant can provide all the necessary information for successful wayfinding within fractions of a second. Then, all we have to do is to follow the predetermined route as indicated. What sounds like a relatively simple task can cause difficulties if a navigator fails to interact with the navigation aid on a regular basis.

In this thesis, I investigated the influence of different stress induction approaches on navigation performance by analyzing pedestrian tracking data collected in virtual urban environments. Results show that different types of stressors had different impacts on navigation performance. Applying time pressure on study participants did not result in navigators reaching the destination faster. On the other hand, participants performing a concurrent spatial tapping task had significantly longer to get from a starting point to a predefined destination.

I also found mixed evidence of a learning effect with increasing task experience. Furthermore, I reproduced and examined recorded route deviations before categorizing them into a deliberate and an unintended off-track group. The immediate surroundings of intersections were identified as being prone to unintentional route deviations. In addition, the type of intersection played a crucial role in deviation frequencies. Lastly, a connection between map retrieval and unintended route deviations was determined.

In summary, this work has identified a number of behavioral patterns in pedestrian route-following performance that could be adapted to real-world navigation systems to minimize route deviations and create an enhanced user experience.

Contents

List of Figures

ACKNOWLEDGMENTS

First and foremost, I would like to take the opportunity to thank those people who played a crucial role not only in the scope of this work but also throughout my many years of studies. Without you, I would not have been able to complete this research and acquire my master's degree. Thank you very much for having faith in me!

I would like to express my sincere gratitude to my supervisor, Prof. Dr. Sara Irina Fabrikant, for her trust and encouragement during the last six months. I could not have asked for a more caring, thoughtful, and supporting supervisor to guide me through this journey. A special thanks also goes to Dr. Sascha Credé, who initialized this work by providing access to the vast datasets collected for his dissertation.

Other members of the Department of Geography at the University of Zurich were involved in the working process of this thesis and helped me achieve different milestones. Thank you, Prof. Dr. Robert Weibel and Dr. Stefan Ivanovic, for providing me with detailed feedback and advice following the project proposal presentation. I am equally thankful to Dr. Ian Tanner Ruginski for sharing his knowledge about statistics and providing me assistance with technical issues.

Furthermore, I would like to extend my deepest gratitude to my parents, Monika and Werner, for everything they have taught me, their invaluable support, and their patience.

Thank you, Lisa, for always believing in me, for providing greatly appreciated emotional support, for all the encouraging hugs, and for putting up with me throughout this entire process. Last but not least, thank you, Beat and Brigitta, for letting me stay in your vacation home in the beautiful Swiss Alps, ensuring a calm and pleasant working atmosphere.

CHAPTER 1

INTRODUCTION

Imagine being on your way to a business meeting in an unfamiliar city, using public transportation. You eventually arrive at the designated train station, covering the last section of your journey on foot. Since you are not familiar with your surroundings, you rely on a track-up navigation aid on your mobile device which displays the route to your final destination. With the broad availability of online route planning services offering detailed route descriptions based on real-time traffic conditions, this seems to be an easily manageable task.

However, without wishing to offend anyone reading this thesis, I would suggest that all of us have gotten lost in an unknown city environment despite using the most modern navigation aid technology. For various reasons, such as inattention, distraction, or disorientation, you failed to follow the path indicated by the navigation aid, resulting in a deviation from the predetermined route. Usually, you do not immediately realize that you have gone astray until you consult your navigation aid again. Then you make a 180-degree turn and return to the predetermined route from where you continue your journey.

Your navigation performance might get negatively affected in situations with additionally induced stress, such as time pressure or increased workload. In our example, time pressure could result from your train arriving late, while increased workload could be caused by thinking through the last couple of details of the upcoming meeting while talking to a friend and trying to navigate through the environment. After all, you want to reach your destination as quickly and as efficiently as possible without taking any unnecessary detours.

1.1 Aims & Motivation

This thesis analyzes the influence of stress induction approaches (time pressure/increased workload) on navigation performance by evaluating two datasets collected separately in virtual reality experiments. In these two studies, participants had to walk through an urban environment by following a predetermined route and reach a given destination. Study participants were asked to complete the navigation task as quickly as possible while memorizing relative locations of highlighted landmarks within the environment. Neither of the two tasks was supposed to be given preferential attention (Credé, Thrash, Hölscher, & Fabrikant, 2019, 2020).

This work investigates the circumstances that led to study participants going astray from the predetermined route, resulting in so-called off-track events. To do this, every event was split into either an unintended or deliberate deviation group after reproducing the trajectories recorded between the event's initiation and its revocation after returning to the predetermined route.

A precise categorization and quantification of these off-track events could contribute to more enhanced interaction between the navigation aid, its user, and the environment. A smart navigation aid system could benefit from being able to differentiate between a deliberate and an unintended off-track event in many ways. If, for example, a navigation system can interpret the behavior of the user and detects a route deviation that a certain number of individuals has already taken, this could imply the existence of a real-world shortcut, such as a small path over an open green area or park. Consequently, this shortcut could be added to the database and integrated into future route suggestions. This also applies to detours deliberately taken by navigators due to large construction sites blocking sidewalks.

On the other hand, a navigation system could identify crucial locations with an accumulation of unintended off-track events. Depending on the reason that causes pedestrians to deviate from the predetermined route, various measures can be adopted to prevent them from happening. For example, suppose the major cause is identified as a distraction due to a nearby historic site. In that case, the navigation system could issue an acoustic or haptic warning to get the user's attention. However, if navigators go astray at confusing intersections or busy train stations, the navigation aid could enhance the route display by providing more detailed instructions with a higher resolution.

Moreover, the environment could benefit from smart navigation systems by adapting real-world signposts at crucially classified intersections for pedestrians both with and without a navigation aid. Early detection of dangerous sites may even prevent accidents triggered by knee-jerk reactions as a consequence of unintended off-track events.

By estimating the impact of different stress induction approaches on navigation performance, a smart navigation system could also adapt to the user's spatial cognition abilities. Depending on the individual's navigational skills, working load capacity, or state of distress, the system could intervene more frequently for poorer performance users. Additional information such as familiarity with the urban environment, the purpose of the journey, time of the day, weather conditions, or local recommendations could also be included.

With this thesis, I want to contribute a small part to the development of future smart navigation systems that can provide more efficient route suggestions tailored to suit each user's needs.

1.2 Research Questions

Three research questions were addressed in the present study. The first research question covers the influence of induced stress factors on navigation performance. Secondly, study participants' performance across the whole experiment is analyzed to examine possible learning effects. Lastly, causes and effects of unintended route-following errors are evaluated carefully.

Research Question 1:

How do stress induction approaches affect pedestrian navigation performance in virtual reality?

Research Question 2:

How does participants' navigation performance change with increasing task experience?

Research Question 3:

What are the reasons that navigators unintentionally deviate from a predetermined route?

Before stating corresponding hypotheses on these research questions, I first want to provide an overview of related studies addressing navigation under stress induction approaches and explain the experimental variables in the collected datasets. The hypotheses can be found in section 3.3.

1.3 Thesis Overview

In Chapter 1, I have identified three main research questions revolving around navigation performance and provided a number of typical applications for smart navigation systems.

Chapter 2 gives an overview of scientific research in human navigation and aided wayfinding. A navigational tool taxonomy is presented to identify the type of navigation aid users had access to in the experimental setup. Furthermore, I will explain route following and elucidate the difference between decision points and decision scenes. Following a short introduction into route deviations, I will focus on different stress induction approaches and give an overview of previous research investigating the impact of different stressors on human wayfinding tasks. Finally, this chapter concludes with the localization of research gaps.

Chapter 3 explains the experimental procedures of two separate user studies conducted by Dr. Sascha Credé, who kindly offered two datasets collected in a virtual urban environment to be used in this work. Furthermore, I will define navigation performance within the scope of this thesis and establish hypotheses for the previously stated research questions.

In Chapter 4, I will depict the methods used to process, analyze, and evaluate the available data before depicting different intersection types that were found in the virtual city environments. This chapter concludes with an overview of applied statistical analyses.

Chapter 5 reports all statistical tests conducted in this thesis and delivers corresponding results to the three research questions.

In Chapter 6, results from statistical analyses are discussed, summarized, and compared to previous studies. This chapter also checks if the initial hypotheses are valid.

CHAPTER 2

LITERATURE REVIEW

2.1 Human Navigation

Moving through space from a current location to a distinct destination is one of the most common spatial tasks for a human being. Whether an individual is taking just a few steps within an apartment to use the bathroom or traveling around the world on sabbatical leave, the spectrum of the involved spatio-temporal scale can vary immensely (Montello & Sas, 2006). Thus, the scope of participating research fields is manifold and includes scientists with a geographical, psychological, or neuroscience background (Denis, 2017). This leads to various definitions for the term "navigation" (Allen, 1999; Downs & Stea, 1977; Kuipers, 2000; Montello, 2005); I will focus on the latter.

The process of coordinated and goal-directed movement across an environment is known as navigation and includes two components labeled locomotion and wayfinding (Montello, 2005). The term "locomotion" is described as the actual movement task with respect to the surroundings. It involves both sensory and motor systems to identify and avoid obstacles along the current path. In other words, coordinated body movement is the basis for locomotion and is done mostly automatically (e.g., standing upright, movement of legs for walking, or avoiding objects).

The term "wayfinding" is the planning part of navigation that includes a destination, typically located outside the immediate perceptual field, and a plan for how to reach it efficiently. This task is more effortful and requires information about the environment, stored either internally or externally (Montello & Sas, 2006). Internal representations are composed of acquired knowledge of the traveler's surroundings or other people, while external representations comprise any kind of navigation aids or map artifacts. Wiener, Büchner, & Hölscher (2009) identified the spatial knowledge of a navigator as a critical factor of navigation.

In theory, both locomotion and wayfinding can occur separately (Montello & Sas, 2006). Planning a hike without ever taking it would be an example of just wayfinding. On the other hand, strolling around without the intention to reach a particular destination can be described as locomotion only. Both components are required to complete a successful navigation task. However, since wayfinding is the cognitive component of navigation, I will focus on this term.

Wiener et al. (2009) further distinguish between aided and unaided wayfinding due to these two approaches' fundamentally different cognitive demands. Unaided wayfinding requires the absence of externalized wayfinding aid and therefore only relies on an individual's mental spatial knowledge of an environment. Unaided wayfinding is further subdivided depending on the presence of destination knowledge, route knowledge, and survey knowledge.

2.2 Aided Wayfinding

During aided wayfinding, on the other hand, navigators have access to wayfinding assistance in some form of static or dynamic externalized representations such as signs, maps, or navigational assistants (Wiener et al., 2009). Each of these representations requires different cognitive abilities starting with the depiction of information and information delivery.

Sign-following or trail-following is a navigation task requiring low cognitive effort (e.g., exiting an airplane and navigating to the baggage claim). If signage is present visibly and legibly at every decision point, there is almost no chance of unintentionally getting lost (Raubal, 2001).

In contrast, maps usually contain a more significant amount of information. However, their effectiveness for wayfinding is highly dependent on how well an individual can read, process, and use them to complete a navigation task successfully. This includes symbol identification, self-localization, orientation, and path integration (Lobben, 2004). Graf & Schmid (2010) pointed out that maps exist in various shapes, sizes, and dimensions (e.g., paper maps, static maps, or mobile maps).

Finally, navigational assistants that provide spatial information for portable devices anywhere and anytime have become ubiquitous with smartphones' advancement (Gartner, Huang, Millonig, Schmidt, & Ortag (2011). They can depict track-up navigation instructions on demand, fitted to a user's needs (Corona & Winter, 2001).

Routes can also be communicated verbally as route directions (Lovelace, Hegarty, & Montello, 1999), procedural discourse (Tom & Denis, 2003), destination description (Tomko & Winter, 2009), or a combination of these approaches. The quality and comprehension of these instructions are decisive for successful navigation, as Allen (1997) discussed.

The overall amount of cognitive effort needed from a navigator to successfully complete an aided wayfinding task is highly dependent on the type of representation (Wiener et al., 2009) but generally lower compared to an unaided wayfinding task, as stated by Schrom-Feiertag, Stubenschrott, Regal, Schrammel, & Settgast (2016). Besides, aided wayfinding may highly depend on the environment in which a navigation task is performed (Frank, 2009). Frank (2009) also suggests to further distinguish between different aided wayfinding tasks depending on destination knowledge. Dalton, Hölscher, & Montello (2019) point out that an individual's navigation task in complex environments is further influenced by social activity such as interacting with or co-presence of other individuals.

2.3 Navigational Assistants

Nowadays, suppose individuals find themselves in an unfamiliar environment and want to get from point A (their current location) to point B (a destination not within the immediate surroundings). In that case, they usually rely on a navigation aid in the form of a digital navigational assistant on their mobile phones. The assistant will then calculate and generate the most efficient route based on the environment's path network (Richter, 2008).

Chen & Stanney (1999) proposed a navigational tool taxonomy that organizes navigational tools into five functional categories (see Figure 1). These tools can:

1. map the current position of the navigator,
2. display the current orientation of the navigator,
3. log the movements of the navigator,
4. demonstrate surrounding environmental information,
5. present active guidance for the navigator.

Today, commonly used navigation aids are classified as category 5 tools since they fulfill all requirements listed above. Users of a tool in this category simply need to follow the assistant's directions without making their navigational plans. The mental effort required to reach a given destination is minimal compared to tools of lower categories (Chen & Stanney, 1999).

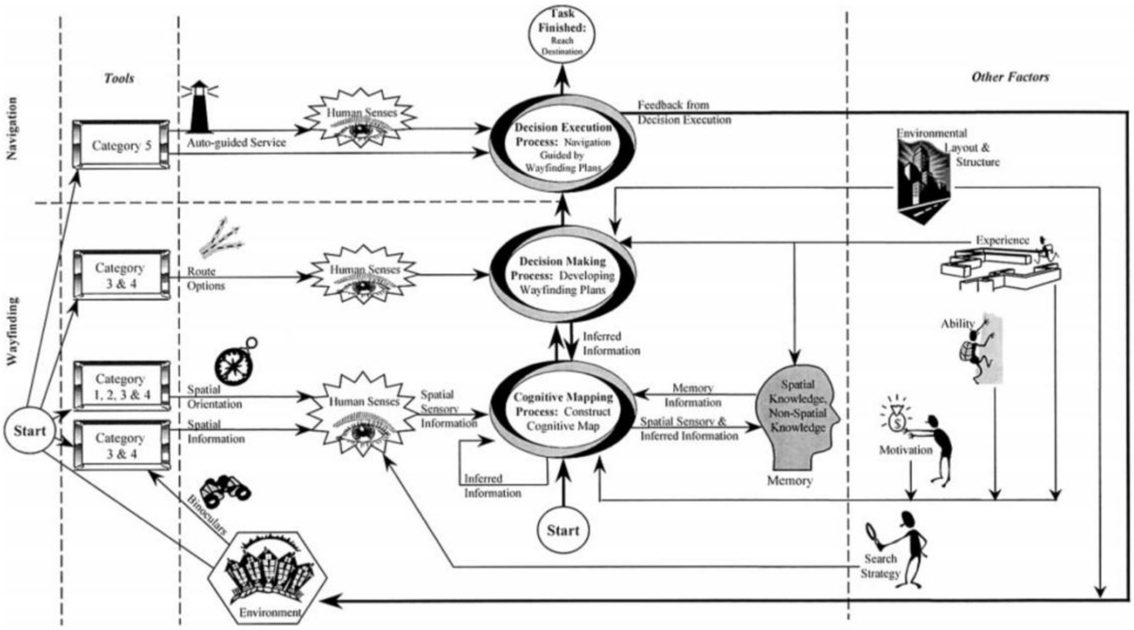


Figure 1: The influence of navigational tools on wayfinding (Chen & Stanney, 1999).

But however good these fully equipped navigation aids seem to be, there is always another side to the coin. By totally relying on navigation technology, a navigator will find himself completely lost in case of a navigation system malfunction, power failure, or missing mobile network coverage. In moments like these, previously acquired spatial knowledge of the surroundings is a genuine asset. Different researchers have examined the effect of wayfinding tools on spatial knowledge acquisition (Thorndyke & Hayes-Roth, 1982; Gillner & Mallot, 1998; Richardson, Montello, & Hegarty, 1999).

Furthermore, suppose an individual has some preexisting knowledge about an environment. In that case, a depicted route's mental processing will demand reduced working memory, therefore decreasing divided attention and increasing spatial awareness (Gardony, Brunyé, Mahoney, & Taylor, 2013).

Nevertheless, when used with certain diligence, navigational assistants can ease everyday life, especially for people with different physical disabilities (Goodwin, Sanders, Poland, & Stott, 1997; Bohonos, Lee, Malik, Thai, & Manduchi, 2007).

2.4 Route Following

The task of performing actions based on information provided by a navigation aid is known as "route following" and thus is a specific kind of (aided) wayfinding (Richter, 2008). Performing a route-following task requires locomotion since individuals constantly monitor their local surroundings (Gartner et al., 2011). It is essential to mention that route following can also be used for unaided wayfinding tasks, as shown by Brügger, Richter, & Fabrikant (2018). However, in this thesis, I will use this term only in connection with aided wayfinding.

In a navigation context, the term "route" is used for behavioral patterns consisting of route segments, decision points, and two endpoints. These endpoints indicate the origin and the destination of the route. "Paths", on the other hand, are unbounded, linear, and physical entities. They comprise branching points and path segments chosen from a path network (Klippel, 2003). Route segments and path-segments, as well as decision points and branching points, correspond to each other but on a different level: While the former are conceptualized on a functional level, the latter are combined on a structural level (Richter, 2008). Another feature that distinguishes routes from paths is direction, as pointed out by Richter (2008): While routes are always directed in one way or another, paths do not comprise any direction. Therefore, the most efficient route from point A to point B might not turn out to be the most efficient route when reversed.

2.5 Decision Points and Decision Scenes

Decision points also often referred in the literature to as nodes, or intersections as perceived in a real-world environment have been identified by Janzen & Hawlik (2005) as crucial during route following. These are locations where navigators must decide which path they want to continue. Intersections along a route are considered decision points independently of a navigator's behavior. Whether an individual is walking straight or making a turn, there is always a decision to be made (Janzen & Hawlik, 2005).

Moreover, the number of branches and their average deviation from prototypical angles play an essential role in calculating decision point complexity. Oblique turns far from standard angles of 45 or 90 degrees demand more spatial processing (Richter, 2009).

The more complex a decision point is, the greater the chance of a negative impact on the navigation performance (O'Neill, 1991). In other terms, decision points are predestined for route-following errors, reflecting in route deviations (Richter, 2009). In order to diminish the possibility of route-following errors, researchers have compared the fastest, shortest, simplest, or most regionalized route between different origin and destination pairs (Mark, 1986; Duckham & Kulik, 2003; Richter & Duckham, 2008; Richter, 2009).

Gaisbauer & Frank (2008) suggested using the term "decision scenes" instead of "decision points" in conjunction with pedestrian navigation. They argue that pedestrians move with a higher degree of freedom than is considered in many navigation system designs. By expanding the walkable space around decision points, they take into account unconstrained movement behavior in open spaces, which raises the accuracy of navigation aids. Thus, decision scenes are characterized as the local vista space around a particular decision point (Gaisbauer & Frank, 2008).

2.6 Route Deviations

For various reasons, a navigator performing a route-following task from an origin to a destination may go astray and end up on a path segment that was not intended to be part of the route. As described in the previous section, most of these route deviations occur at intersections. However, deviations can also happen on a single route segment, predominantly in less structured environments (Heuten, Henze, Boll, & Pielot, 2008). Schirmer, Hartmann, Bertel, & Echtler (2015) identified two possible error events potentially occurring at intersections: taking a wrong turn (not following the indicated direction) or walking past an intersection (instead of taking a turn). These assumptions only apply when the navigation aid is functioning faultlessly. Otherwise, unsuccessful route-following can be the result of many other reasons as depicted by Golledge (1992) or Brunyé, Gagnon, Gardony, Gopal, Homes, Tylor, and Tenbrink (2015).

2.7 Stress Induction Approaches

We learned that, by definition, humans deal with wayfinding and navigation tasks multiple times per day. Depending on how well we know our surroundings and which navigation aids are available, these tasks can range from extremely simple when going for a walk in the local neighborhood to very demanding in completely unfamiliar environments.

Stress is a feeling that we also encounter every day and can be described as a physical, emotional, or psychological response to some sort of strain. Stress is perceived diversely for different individuals under different conditions and is seen by a majority of the population as negatively impacting work productivity (Fink, 2009).

However, Yerkes & Dodson (1908) proved that a moderate amount of stress could enhance performance for both monotonic and complex tasks (see Figure 2). While the positive inter-correlation of arousal and performance continues for simple tasks, this relationship reverses at some point for difficult tasks, as illustrated by Diamond, Campbell, Park, Halonen, & Zoladz (2007).

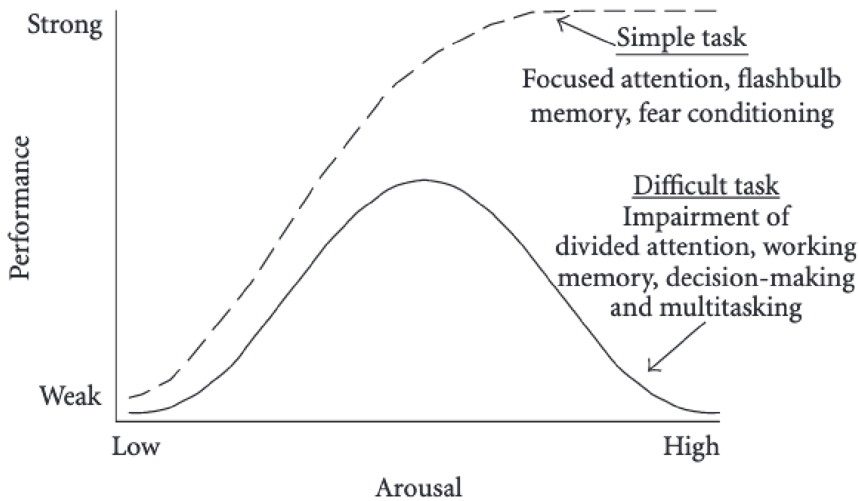


Figure 2: Yerkes-Dodson law, according to Diamond et al. (2007), showing the relationship between arousal and performance.

Several virtual environment studies have investigated the relationship between stress and navigation performance. Duncko, Cornwell, Cui, Merikangas, & Grillon (2007) found positive effects of stress on navigation task performance after exposing participants' hands to ice water, known as the Cold Pressor Test (CPT). They used a Virtual-Navigation Morris Water Task

(VNMWT), where navigators were instructed to locate a hidden platform in a circular pool and reach it as quickly as possible. A trial was evaluated as a failure if participants could not reach the platform within a 60 second time window. The stress group turned out to have significantly fewer failures and showed significantly lower heading errors.

Klopp, Garcia, Schulman, Ward, & Tartar (2012) conducted a very similar experiment (VNMWT) as Duncko et al. (2007) but with a different stressor. Instead of a CPT, participants performed a Trier Social Stress Test (TSST) to exercise social stress. Despite similar experiment setups as Duncko et al. (2007), Klopp et al. (2012) did not find significant differences between the stress and the control groups. It was argued that physiological stressors (CPT) and social stressors (TSST) have mixed effects on human navigation.

Boone (2019) compared various stressors (physiological, social, and cognitive) to evaluate their impacts on navigation efficiency and strategy. Study participants first performed a spatial learning task in a virtual maze by following a predetermined route. Along the route, they passed previously placed objects. Participants were then placed somewhere within that maze and were asked to navigate to the desired object. No experiment showed a significant difference between the stress group and the control group leading to the conclusion that navigation strategy and efficiency are robust to tested stressors' effects.

Brunyé, Wood, Houck, & Taylor (2017) were the first to examine the impact of time pressure as a stressor on a navigation task. In contrast to the previously mentioned studies, Brunyé et al. (2017) induced the stressor during retrieval trials and not before the actual navigation task. Participants visited the laboratory on two consecutive days. During the first session, they were exploring and learning landmarks in a virtual environment. Then, on the next day, participants had to find their way from one fixed landmark to another under different time pressure conditions. It was found that with increasing time pressure, navigators relied more on familiar, previously walked path segments instead of traveling in the global direction of the goal location using shortcuts.

Finally, Credé et al. (2019; 2020) conducted two separate virtual-reality experiments where participants had to follow a predetermined route using a navigation aid and reach a given destination as quickly as possible. During the navigation task, local and global landmarks were encountered in the urban environment. After each navigation session, spatial knowledge was assessed by testing the accuracy of these landmarks' relative locations. Different stress induction approaches were chosen for the two studies. Credé et al. (2019) employed time pressure on half of the participants, while Credé et al. (2020) applied increased workload to manipulate stress by adding a spatial tapping task. Results showed no impairments for survey knowledge acquisition under time pressure. However, the second study revealed a negative impact of concurrent task demands for survey knowledge acquisition. These findings indicate that the type of stressor is crucial to compromised working memory.

2.8 Research Gap

Looking at the literature, it becomes evident that the influence of stress on human navigation is highly dependent on the type of the induced stressor and the navigation task. Different stress induction approaches may lead to entirely different results for the same navigation task. On the other hand, changing the navigation task under consistent stress might also alter the outcome of navigation performance. Other variables such as previously acquired knowledge about the environment where the navigation task takes place, or whether stress is induced before or during navigation, also impact navigation performance. Furthermore, individuals' reactions to stress can vary immensely and involve complex physiological and psychological processes (Noack, Nolte, Nieratschker, Habel, & Derntl, 2019).

To my knowledge, no previous studies have examined pedestrians' navigation performance in a previously unknown urban environment using a category 5 navigational tool (see Section 2.3) under different stress induction approaches. This thesis aims to close this gap for time pressure and increased workload by analyzing human movement patterns collected in virtual-reality experiments by Credé et al. (2019; 2020).

CHAPTER 3

METHODOLOGY

This section will give an overview of the experimental procedure carried out by Dr. Sascha Credé. Within the scope of his doctoral thesis, Credé (2019) conducted two virtual-reality experiments to assess navigators' capabilities to acquire spatial knowledge from local and global landmark configurations in situations with and without stress. In both experiments, stress was employed on half of the study participants in the form of time pressure (Study I) and increased workload (Study II). The overview of the experimental procedure is limited to the relevant approach (i.e., the navigation task) in the context of this thesis. For a detailed technical implementation of the experimental setup, please refer to Credé (2019).

Furthermore, I will define navigation performance based on the available data and explain the distinction of off-track events after reproducing participants' trajectories. After elucidating the experimental conditions, I will address the hypotheses to the corresponding research questions.

3.1 Experimental Procedure

Both experiments took place in the CAVE (i.e., Cave Automatic Virtual Environment) at the Department of Geography at the University of Zurich. For the egocentric navigation task, study participants were placed on a chair in a room surrounded by projection screens on three sides, wearing 3D shutter glasses. Subjects were instructed to perform two concurrent tasks in an unfamiliar virtual environment comprising a navigation task and a spatial learning task. In addition, they were explicitly briefed not to prioritize one task over the other, as they were of equal importance.

3.1.1 Navigation Task

After being familiarized with the experimental procedure by means of a training phase, participants found themselves on a virtual train entering a train station. As soon as the train came to a full stop, subjects' first-person perspective viewpoint was automatically shifted out of the train to the starting location from where the navigation task began.

The navigation task consisted of following a predetermined route using a navigational assistant to reach a predefined destination. Participants could display the track-up navigation aid in the form of a planimetric 2D map (see Figure 3) by pressing a button. Toggling between the navigation task and the navigation aid was not restricted regarding frequency or duration. However, movement across the virtual environment was disabled during navigation aid display and until a few seconds after map usage (see Section 3.1.7). Furthermore, participants were advised to always stay on track and finish the navigation task as quickly as possible.

Figure 3: A section of the track-up navigation aid route display from Study I. The map is centered at the navigator's current position (red triangle). The dotted blue line with white arrows indicates the route to the destination, marked as a blue circle (Credé et al., 2019).

3.1.2 Spatial Learning Task

While performing the route-following task, participants were instructed to remember highlighted buildings' relative locations, referred to as the spatial learning task. These buildings were distinguishable from their surroundings because of their bright colors. Depending on their height, buildings were either classified as local (low-rise) or global (high-rise) landmarks. From a navigator's perspective, multiple global landmarks could be seen from locations along the route, whereas local landmarks' visibility was restricted to their immediate surroundings. A set of landmarks consisted of four highlighted buildings, although this number was not communicated to the study participants before the experiment.

The local landmark configuration in both studies consisted of four highlighted low-rise buildings that were placed along the route. For the global landmark configuration, highlighted skyscrapers were placed in the distance for Study I. In Study II, however, participants also walked directly by global landmarks as they were placed next to the predetermined route. Study I contained an additional mixed landmark configuration where both previously mentioned sets of landmarks were visible, but only the local landmarks were highlighted (see Figure 4).

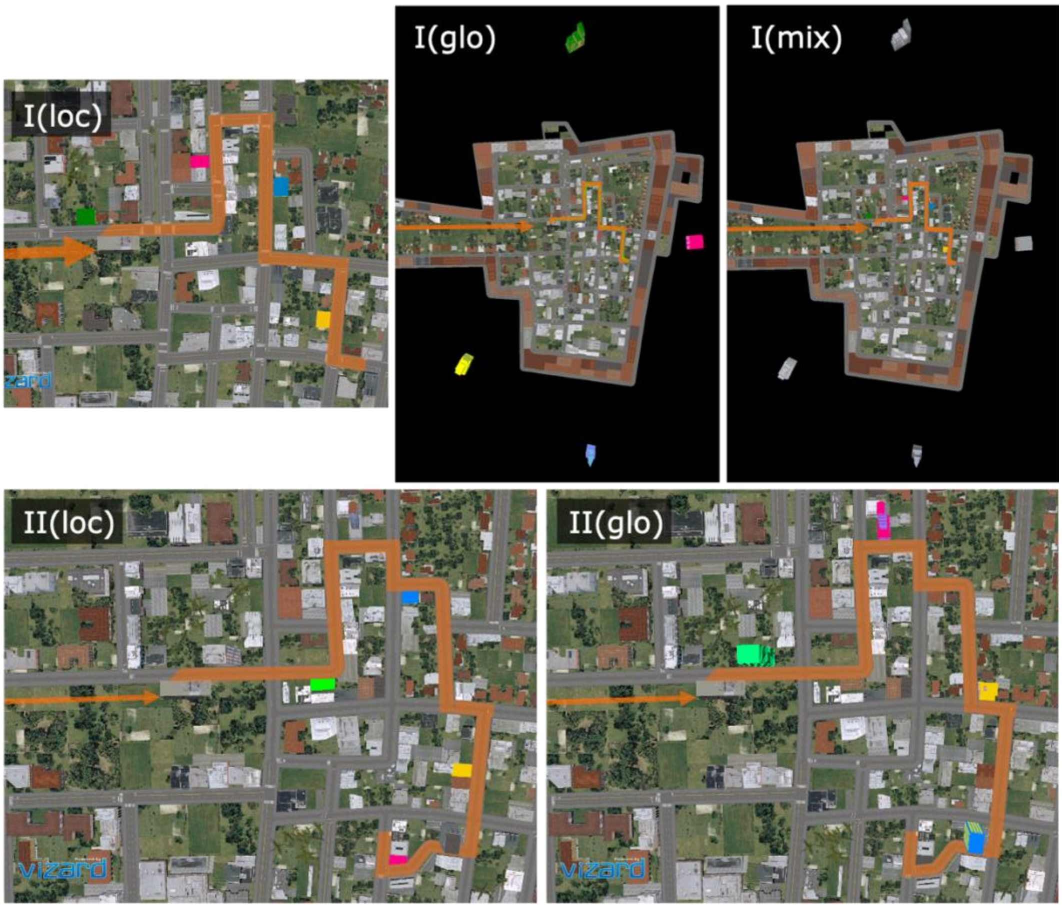


Figure 4: Bird's-eye perspective of different landmark configurations of one city model each from Study I and II. Highlighted landmarks are depicted in bright colors. Participants arrived at the train station (orange arrow) from where they started the route-following task (orange line). I(loc) & II(loc) In the local landmark conditions, landmarks were placed along the route. I(glo) Global landmarks were located in the distance. II(glo) In contrast, global landmarks were also placed along the route. I(mix) The mixed landmark condition contained highlighted landmarks as in I(loc) and unmarked global landmarks in the distance.

3.1.3 Stress Manipulation

Half of the study participants were randomly assigned to either the stress group or no stress group before the experiment started. In Study I, time pressure was manipulated by introducing two scores, only one of which was related to the navigation task. This score began at 100 points. One point was deducted for every 10 seconds while participants were navigating. Every time after losing 10 points, the current score was highlighted, and a beeping noise was sounded. Participants were also told that their scores would influence their monetary compensation for participating in the experiment. Study II was designed similarly regarding stress manipulation. Furthermore, an additional spatial tapping task was introduced, for which subjects assigned to the stress group had to repeatedly and continuously type a given series of six numbers on a 3x3 matrix numeric pad. The overall score was negatively affected if the tapping rate fell below one keystroke per second or if the numbers were entered in the wrong order.

3.1.4 Design

Three different city models were designed for Study I. All routes to be navigated started at the train station and consisted of three left and three right turns. Participants performed three rounds in three different city models that each contained one out of three landmark conditions in a counterbalanced order (see Figure 5). They did not have to comply with traffic rules and could move freely between streets or sidewalks.

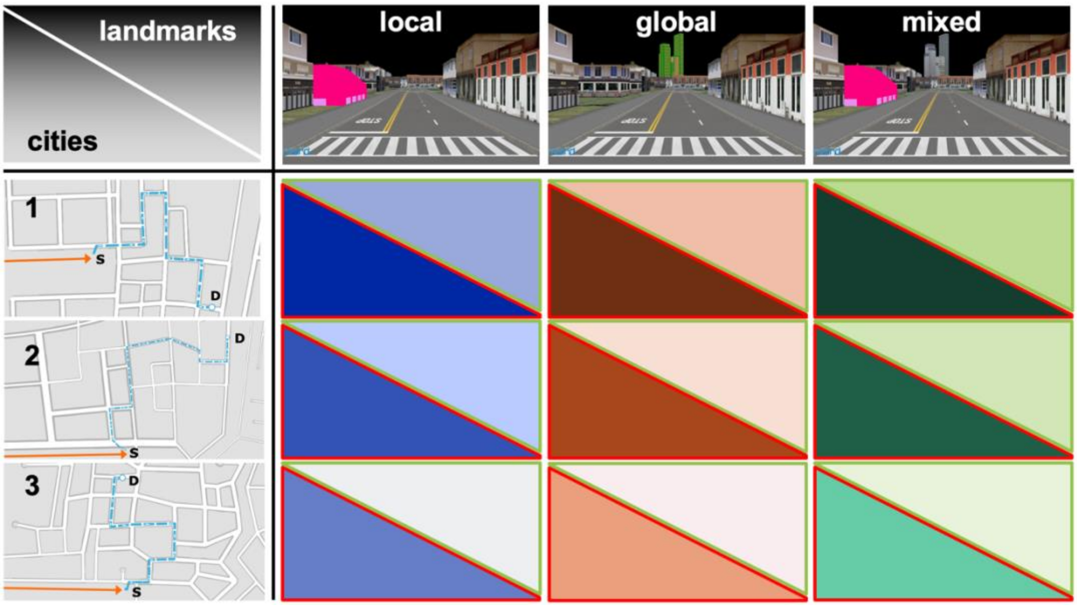


Figure 5: Representation of the 3x3x2 matrix of the experimental setup of Study I. Displayed on top are the three different landmark configurations, i.e., local (highlighted low-rise buildings), global (highlighted high-rise buildings), and mixed (highlighted low-rise buildings with visible high-rise buildings). The three city models on the left depict the train rides (orange lines), the navigation routes (blue dotted lines), their origins (S), and destinations (D). The darker triangles with red frames represent time pressure induction, while the lighter triangles with green frames stand for no impairments of stress induction approaches.

Two new city models were created for Study II. Subjects in this experiment conducted two rounds in two different city models containing either a local or global set of landmarks (see Figure 6). The order was counterbalanced across participants. In contrast to Study I, the number of left and right turns in this study did not correspond between city models.

In both studies, movement speed was capped at 3.8m/s, and participants were usually going full speed unless they were consulting the navigation aid. This value was obtained after an evaluation of what speed of movement was perceived as pleasant in these virtual environments. Since a large scale was implemented for buildings heights and street widths, this rate of speed cannot be adopted in a real-world navigation task under the present circumstances.

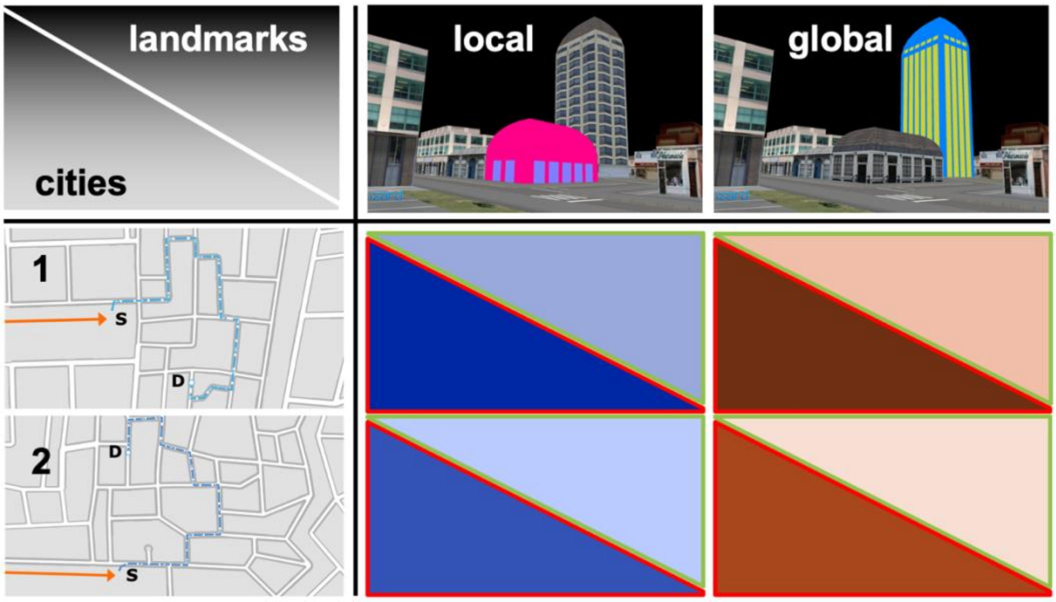


Figure 6: Graphic illustration of the experimental setup of Study II, showing a 2x2x2 matrix. Landmark configurations are visualized on top. Note that all buildings are present in both configurations. On the left are the street networks of the two city models. The orange arrows indicate the trains' arriving direction. The walkable route is depicted as a blue dotted line from its origin (S) to its destination (D). Darker, red-framed triangles represent the influence of an additional tapping task, whereas lighter, green-framed triangles indicate no additional stress induction.

3.1.5 Technical Modifications between Experiments

The two experiments were conducted separately (i.e., 01/2017 through 06/2017 for Study I and 11/2017 through 01/2018 for Study II). After the evaluation of results from Study I, further modifications were made for Study II apart from those involving the spatial learning task or stress induction approaches. The following technical modifications are of importance for this thesis:

- The navigation control interface changed from a one-handed joystick device used in Study I to a foot-operated motion controller introduced in Study II. Thus, participants in the stress group were able to utilize their dominant hand for the tapping task. In view of the fact that all participants practiced using the navigation control interface in a training phase prior to the main experiment, this modification is not expected to have influenced navigation behavior. Moreover, all subjects were seated during the navigation task, with the result that physical movement was absent, and participants had to rely on visual cues only.

- The navigation aid's map scale changed from 1:106 (section of 0.071 km^2) in Study I to 1:156 (section of 0.026 km^2) in Study II. Therefore, when participants in the latter study were consulting the navigation aid, not only was the corresponding section of the city environment smaller, but the route was also shorter. For two identical navigation tasks, displaying a smaller section of a route could automatically lead to more frequent map consultations assuming that navigators could memorize the route to the edge of the display before the map was retrieved again.
- In both studies, movement through the virtual environment was disabled after map usage. However, this restriction was reduced from five seconds in Study I to three seconds in Study II. Therefore, participants in the latter study were able to move two seconds earlier and did not lose as much time between map usage and the navigation task's resumption. This modification in favor of participants in the second study could offset the disadvantage described in the previous point.
- A disparity was also found in both studies' recordings of timestamp intervals. On average, participants' movements were logged every 28 milliseconds. However, these values differ considerably between runs. For example, average intervals ranged between 16 and 33 milliseconds when comparing individual runs. This means that in extreme cases, some recordings have more than double the resolution compared to others. Despite this discrepancy, both studies' movement data are of excellent precision that can only be achieved under virtual-reality conditions. Both datasets surpass the requirements for this thesis.

3.1.6 Data Logging

During every run, participants' raw tracking data was written and saved on a single logfile. The recordings started after the train ride when navigators took over the controls of their virtual avatar and ended as soon as the destination was reached. Each line began

```
marker;2017-05-17 09:59:41.509000;navigation_START;trial_number: 1;condition_lm: local;condition_stress: False; city: Resources/city_1/model/env1.osgb
marker;2017-05-17 09:59:41.509000;on_Track
tracker;2017-05-17 09:59:41.509000;transport_node;-597.480407715;0.913072943687;823.735107422;59.5296669006;0.0;0.0
tracker;2017-05-17 09:59:41.509000;head_node;-0.0934265181422;1.21150064468;-0.418295443058;-14.9233522415;5.53030510275e-08;-4.37923049927
[…]
tracker;2017-05-17 09:59:52.826000;transport_node;-597.729431152;0.5;827.973632812;-5.94735622406;-0.0;0.0
tracker;2017-05-17 09:59:52.826000;head_node;-0.0524651557207;1.20706629753;-0.407690882683;10.1596336365;-1.8750696551e-09;-1.81218540668
marker;2017-05-17 09:59:52.855000;show_Map
tracker;2017-05-17 09:59:52.863000;transport_node;-597.729431152;0.5;827.973632812;-5.94735622406;-0.0;0.0
tracker;2017-05-17 09:59:52.863000;head_node;-0.0529001690447;1.20718836784;-0.408884912729;10.0452547073;-4.35428493262e-09;-1.76658439636
[…]
tracker;2017-05-17 09:59:55.984000;transport_node;-597.939025879;0.5;829.985839844;-5.94735622406;0.0;0.0
tracker;2017-05-17 09:59:55.984000;head_node;-0.025282278657;1.2101559639;-0.416889548302;22.4963970184;5.64800757274e-08;-5.0031003952
marker;2017-05-17 09:59:56.019000;hide_Map
tracker;2017-05-17 09:59:56.023000;transport_node;-597.939025879;0.5;829.985839844;-5.94735622406;0.0;0.0
tracker;2017-05-17 09:59:56.023000;head_node;-0.0252894870937;1.21015906334;-0.41688477993;22.4980888367;4.18540331282e-08;-5.0054731369
[…]
tracker;2017-05-17 10:00:36.501000;transport_node;-472.360107422;0.5;862.87902832;69.4569015503;-0.0;0.0
tracker;2017-05-17 10:00:36.501000;head_node;-0.0499040409923;1.20925319195;-0.404329687357;3.53658008575;4.31671187684e-09;-5.26578807831
marker;2017-05-17 10:00:36.508000;off_Track
tracker;2017-05-17 10:00:36.526000;transport_node;-472.26940918;0.5;862.912841797;69.4233093262;-0.0;0.0
tracker;2017-05-17 10:00:36.526000;head_node;-0.0499040409923;1.20925319195;-0.404329687357;3.53658008575;4.31671187684e-09;-5.26578807831
[…]
tracker;2017-05-17 10:00:38.934000;transport_node;-464.916809082;0.5;866.739868164;45.8629302979;-0.0;0.0
tracker;2017-05-17 10:00:38.934000;head_node;-0.0861256048083;1.20169568062;-0.407372355461;-13.0498971939;1.98123695228e-09;-0.429664850235
marker;2017-05-17 10:00:38.941000;on_Track
tracker;2017-05-17 10:00:38.957000;transport_node;-464.855651855;0.5;866.799926758;45.414932251;-0.0;0.0
tracker;2017-05-17 10:00:38.957000;head_node;-0.0861256048083;1.20169568062;-0.407372355461;-13.0498971939;1.98123695228e-09;-0.429664850235
tracker;2017-05-17 10:00:38.977000;transport_node;-464.800018311;0.5;866.85534668;45.0046844482;-0.0;0.0
[…]
marker;2017-05-17 10:03:20.273000;Navigation_END
```

Figure 7: Summary of a log file's components. The first and last lines contain technical information of the experimental setup and are accentuated in green color. On- and off-track events are depicted in red color. Show- and hide-map events appear in purple. The vast majority of lines contain positioning and orientation information (yellow color). This participant took 218.764s to conduct the navigation task. In this time frame, 18,967 lines of high-resolution tracking data were written to the log file.

with either a tracker or marker note. All values were separated by semicolons (see Figure 7).

Recorded tracker values were divided into transport nodes and head nodes and separated by paragraphs. Therefore, lines alternated between these two measurements. Every line contained a timestamp with date and time specified in milliseconds. In addition, lines containing transport nodes included the navigators' current position determined in the virtual environments' internal x-y-z based coordinate system. Because of the fact that city models were completely flat, one of these values remained constant and was negligible. Against my expectations, the value to be neglected turned out to be the y-axis. The last value depicted from lines containing transport nodes was the navigator's orientation in a range of -180° to 180°. As the name suggests, head nodes comprised participants' head position and orientation, rendered in an x-y-z based coordinate system. These movements were registered by optical sensors mounted in the CAVE that tracked targets attached to the participants' 3D shutter glasses. Values for the head position relative to the rest of the body were negligibly small, bearing in mind that participants were seated during the whole experiment. However, the head's orientation in terms of roll, pitch, and yaw movements was much greater, especially for the latter two values.

On the other hand, lines with marker values contained important information regarding navigation behavior. They listed events in the virtual environment, such as map consultations and track deviations, provided with the corresponding timestamp. As soon as navigators went astray from the predetermined route, a line was inserted in the log file comprising the timestamp and an off-track notice. When participants returned to the route, another line was created, again consisting of the timestamp and the on-track note. The same approach was implemented for show- and hide-map events.

3.1.7 Recordings of Off-Track Events

When navigating in an unknown environment, it is crucial to follow the predetermined route indicated by the navigation aid. If navigators fail to follow these instructions, they will eventually find themselves going astray and, in the worst-case scenario, getting completely lost. In a real-world environment, modern category 5 navigational assistants have various options to prevent and counteract such events. Usually, they will issue an acoustic warning advising the user to return to the predetermined route. However, if navigators continue their journeys on a directed path that was not supposed to be part of the initial route, the navigational assistant will try to find a new route encompassing this path. To do so, it continuously updates its user's location and compares it to the path network in the database.

In the present virtual-reality experiment, the predetermined route was fixed and was implemented without any margins for adjustments. To prevent navigators from getting lost, a warning message appeared on the front screen of the CAVE five seconds after deviating from the predetermined route. The warning consisted of a red flashing message advising the user to return on track.

3.2 Definition of Navigation Performance

Reaching a specific destination is the primary goal of a navigation task in everyday life. With the help of a category 5 navigational tool, it is usually not a question of whether navigators find their intended destination but rather a question of when and how they reach it. Successful and efficient navigation in an unknown environment requires a certain amount of interaction between the navigation aid and its user.

In a real-world urban environment, measuring navigation performance is always bound to limitations such as traffic lights, pedestrian traffic volume, weather, road conditions, or individuals' walking speed. While these limitations can be excluded in a virtual environment, other limitations arise, such as the absence of multi-sensory cues or simulator sickness. Therefore, when comparing navigation behavior or navigation performance, these parameters must be considered.

According to the navigation task requirements in the experimental setup, navigation performance is defined within the scope of this work in such a way that the route-following task is completed as quickly as possible. To achieve this, participants could not unintentionally deviate from the predetermined route, as this would have resulted in a detour. However, to stay on the predetermined route, participants periodically had to retrieve the navigation aid, which cost them valuable time. Accordingly, in order to optimize navigation performance, participants had to find a good mixture of when and for how long they displayed the navigation aid.

3.3 Research Questions & Hypotheses

Based on the literature review and the available data, I would like to address the questions of this thesis again and formulate corresponding hypotheses.

Research Question 1:

> How do stress induction approaches affect pedestrian navigation performance in virtual reality?

Hypothesis 1:

> Participants who were under the influence of stressful navigation conditions reached their destination faster.

Performing a route-following task using a category 5 navigational assistant has been identified as a rather simple task in the spectrum of navigation in an unknown environment. We have also learned that arousal can improve performance to a certain extent before remaining at a static high level for simple tasks. Therefore, I assume that stressful navigation conditions led to less- and shorter use of the navigation aid, which has a positive impact on run duration. Since the navigation routes were equal for all participants, irrespective of stressful contexts, it is expected that the distance traveled does not differ.

Research Question 2:

> How does participants' navigation performance change with increasing task experience?

Hypothesis 2:

> A learning effect is determined with increasing numbers of trials.

Prior to the experiment, study participants conducted a training trial to familiarize them with the apparatus and the experimental tasks. However, certain information was deliberately withheld, such as the number of highlighted buildings in a set of landmarks. Other factors, such as the frequency of map retrieval, adaption to stress induction, or control interface experience, may have generated a learning effect with increasing task experience. This research question addresses this issue by testing the influence of task experience on navigation performance.

Research Question 3:

> What are the reasons that navigators unintentionally deviate from a predetermined route?

Hypothesis 3:

> Route-following errors depend on intersection complexity and the amount of interaction between a navigator and the navigational assistant.

It is expected that chances for unintended route deviations increase when navigators have not been consulting the navigation aid for a certain amount of time. In addition, route deviations are expected to occur more often with increasing intersection complexity.

CHAPTER 4

METHODS

4.1 Data Processing and Exploration

I was granted access to tracking data of 52 participants of Study I (26x time pressure) and 53 participants of Study II (27x increased workload). This led to a total of 262 individual log files given the fact that subjects in the first and second study conducted three and two rounds, respectively. To express it in other numbers, I had 20 hours of tracking data. One participant from Study I (no time pressure group) aborted the experiment in the last round due to slight nausea prior to completing all navigation tasks leaving both datasets unbalanced between the two stress groups.

Python 2.7.5 (van Rossum & Drake, 1995) was used to process and extract the necessary data from these log files for this thesis. After acquiring some basic programming knowledge through the textbook by Sande & Sande (2013), several Python scripts were written with a focus on navigational behavior. For instance, calculated values included run duration, distance covered, average speed, event duration, event sequence, and event intervals. To gain an overview of these factors, an extensive Microsoft Excel spreadsheet, version 16.46, was created to make initial calculations such as minima, maxima, and means.

Other Python scripts were adapted to be rendered with Vizard 6.0 (Santa Barbara, CA: WorldViz LLC.) to reproduce and visualize participants' runs from a first-person, third-person, and bird's-eye view perspective. An active user interface was created to display selected landmarks, map events, and route deviations at the push of a button.

It was found that one of the two routes in Study II was prone to erroneous off-track notifications shortly before participants reached their destination. After carefully reproducing the rounds concerned, these notices were deleted. This step was necessary to prevent misleading interpretations of the sharp rise in detected off-track events in this particular city model.

Other bugs needing fixing included one registered off-track event without a corresponding on-track note (logging anomaly) and one missing off-track note (visualization detection). The logging anomaly most likely happened because one participant stepped slightly off the predetermined route with one foot, leading to an off-track notification. However, visualization showed that this event must have been so short that it was revoked within the same timestamp without issuing a corresponding notice. Therefore, this event was removed from the log file.

The missing off-track note was detected after visualizing participants' individual runs. One subject walked in completely the wrong direction right after exiting the train. For some reason, this deviation did not automatically lead to an off-track notification, causing a time-consuming route-following error. Because this individual was most likely not made aware of the deviation, I decided not to classify this as an off-track event.

4.2 Distinction of Off-Track Events

As we learned in section 3.1.6, route deviations automatically led to an off-track note in the corresponding log file, independently of the duration of the off-track event. A total of 373 off-track events were recorded across the 259 runs of both studies. 99% of them occurred within the immediate surroundings of intersections and only four off-track events were recorded on straight path segments. Considering the five-second rule between the initiation of an off-track event and the issuing of the deviation warning, I expected that navigators needed another five seconds to get back on track, making most of these off-track events last for at least ten seconds. However, it was soon found that many recorded off-track events lasted for only fractions of a second (see Figure 8).

In order to clarify this discrepancy between expectation and reality, all runs were reproduced at once from a bird's-eye view perspective, which required massive computing power due to the very high resolution of the tracking data. To overcome this issue

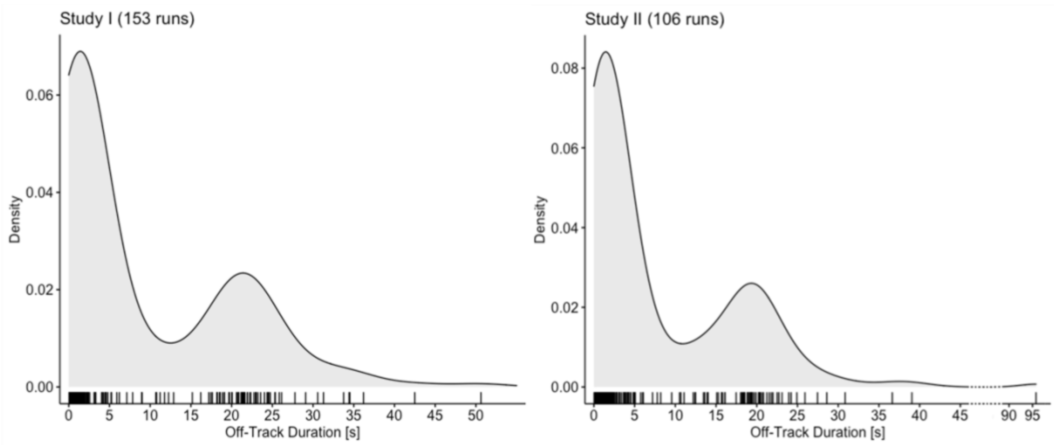


Figure 8: Density plot depicting the duration of all recorded off-track events. Both curves show a distinct bimodal distribution.

Figure 9: Visualization of all 53 participants' tracking data in the second city model of Study II. Each navigator's location is depicted every half a second through a green data point.

when displaying all routes in a city model, only one in twenty data points was visualized, implying approximately one data point per half a second run duration (see Figure 9).

In a second step, recorded off-track nodes were separated from all on-track nodes and highlighted in a distinguishable color. They were depicted in maximized resolution in order to accentuate the partially very short deviations clearly. Besides the obvious deviations that were already visible without color differences, this method also manifested all short-duration deviations. They were mostly found on the inside of curves or intersections, caused by navigators cutting corners across sidewalks' edges (see Figure 10).

Figure 10: Color highlighting of all 101 recorded off-track events in the second city model of Study II.

These findings resulted in a necessary distinction between recorded off-track events, leading to the introduction of an unintended and a deliberate route deviation category. For this purpose, all runs were reproduced separately, and it was decided for every off-track event which category they belonged to. In a second step, I manually added the type of off-track event to the log file for a distinct visualization (see Figure 11).

Figure 11: Off-track events were divided into an unintended (red) or deliberate (orange) category. In this city model, 21 out of 101 off-track events were classified as unintended deviations. Deliberate deviations can be found on the insides of curves or intersections.

Route deviations were classified as unintended if their pattern showed a distinct movement in the wrong direction for a certain amount of time before making a 180-degree turn to get back to the predetermined route. After an unintended off-track event, participants usually re-entered the route near the mark where they had left it, resulting in a distinct U- or V-shaped pattern. In addition, it was found that at the peak of an unintended off-track event, many participants used to consult the navigation aid (in 61% of all occurrences). Together with the comparable lengths of unintended route deviations, this indicates that navigators did not realize that they had gone astray until the warning message popped up on the front screen of the CAVE five seconds after stepping off route. After all, unintended off-track events have a negative effect on navigation performance. Therefore, off-track events along straight path segments were also classified as unintended.

On the other hand, deliberate route deviations can be defined as shortcuts that enhance navigation performance because navigators save time and distance by committing this off-track event. When taking a shortcut across an open green area, it can be assumed that navigators are fully aware of their surroundings and know the immediate route. However, many deliberate off-track events were so short that participants most likely did not realize that they had stepped off track (see Figure 12). The fact that 109 out of 270 classified deliberate off-track events lasted for less than one second leads to the assumption that many participants opted to cut corners as efficiently as possible, merely stepping off track by inches. On the other hand, only 26 out of 270 classified deliberate off-track events lasted longer than five seconds and had the off-track notification pop up on the front screen of the CAVE. These participants were determined to reach the destination as quickly as possible and were not deterred from the flashing warning message.

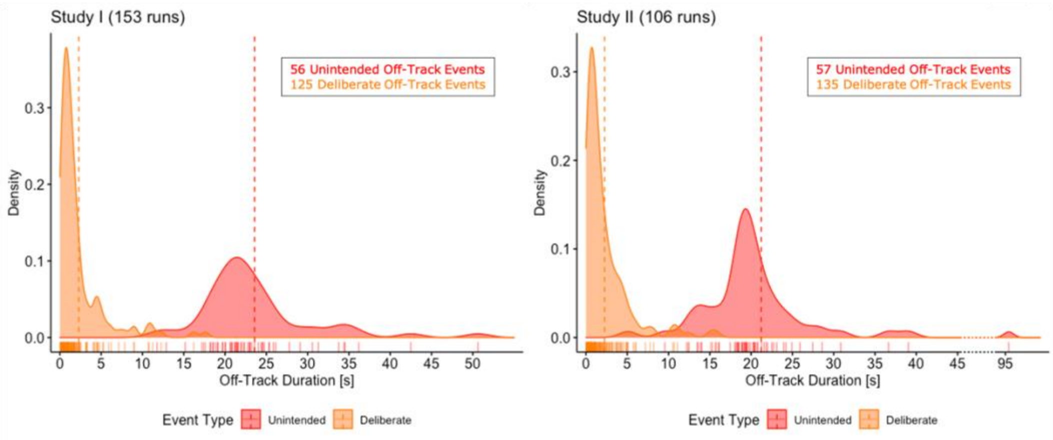


Figure 12: Density plot of recorded off-track events in both studies after classifying them as unintended or deliberate. Absolute off-track numbers are depicted in the textbox.

4.3 Intersection Types

Five different types of intersections with respect to route direction were identified within the scope of this thesis (see Figure 13). At least three path segments (i.e., legs) must intersect in one spot to make up an intersection. All intersections in the five city models that were built for Credé's studies consisted of either three (i.e., T-intersection) or four legs (i.e., X-crossing). An intersection was always approached on one of these legs, giving navigators two and three possible path segments to continue the journey.

At four-leg intersections, navigators always had two options independently of which direction they came from and which direction they intended to go. They could either walk straight or

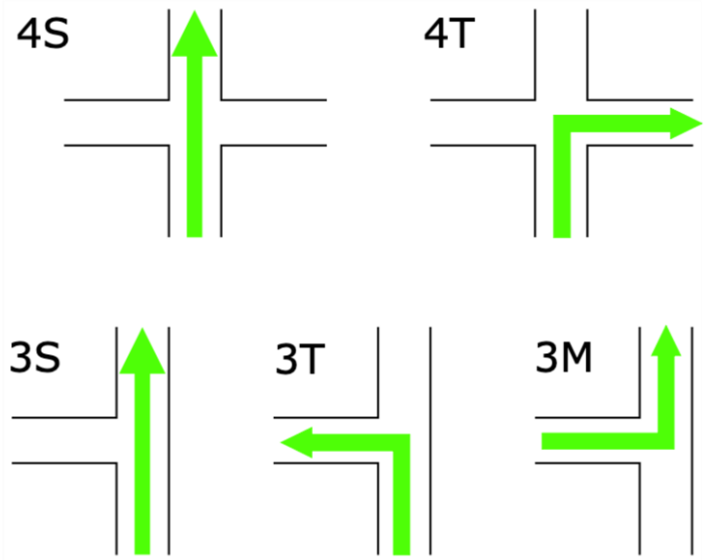


Figure 13: Intersection types with respect to the route (green arrows). All types can be rotated or mirrored freely. At four-leg intersections, navigators could either go straight (4S) or take a turn (4T). For T-intersections, however, directions played a crucial role. Again, navigators could either go straight (3S), deliberately take a turn (3T), or they must take a turn (3M).

take a 90-degree turn. At three-leg intersections, on the other hand, directions were of importance. Again, navigators could either go straight or deliberately take a turn. However, if they came from the path segment without an opposite leg, they had to take a turn (i.e., either left or right).

4.4 Implementation

Statistical analyses were conducted in R version 4.0.3 (R Core Team, 2020). Boxplots and density plots were created with *ggplot2* (version 3.3.3; Wickham, 2011), and *ggpubr* (version 0.4.0; Kassambara, 2020a) packages, respectively. Levene's tests and tests to detect outliers and extreme values were conducted using *rstatix* (version 0.6.0; Kassambara, 2020b) package.

Since both experimental setups are based on a mixed factorial design with between-group and repeated-measures variables, a mixed factorial ANOVA was employed to determine the impact of stress on navigation performance (RQ 1). Thus, the *ezANOVA* function from the *ez*-package (version 4.4-0; Lawrence, 2016) was used according to Field, Miles, & Field (2012). In both studies, the two stress groups were identified as the between-subjects factor and the city models made up the within-subject factor. For Study I, this resulted in a 2 (with time pressure/without time pressure) x 3 (City 1/City 2/City 3) mixed factorial design. Similarly, Study II consisted of a 2 (additional tapping task/no tapping task) x 2 (City 1/City 2) mixed factorial design.

The *lmer* function from the *lme4*-package (version 1.1.26; Bates, Mächler, Bolker, & Walker, 2015) was used to determine possible learning effects with increasing task experience. This approach was chosen because linear mixed-effects models can deal with unbalanced datasets that do not completely cross over. Incorporating the trial number into the analysis added another within-subject factor to both studies, resulting in a 2 (with time pressure/without time pressure) x 3 (City 1/City 2/City 3) x 3 (Run 1/Run 2/Run 3) mixed factorial design for Study I and a 2 (additional tapping task/no tapping task) x 2 (City 1/City 2) x 2 (Run 1/Run 2) mixed factorial design for Study II. For a visualization, refer to Figure 5 (Study I) and Figure 6 (Study II) and replace landmark configuration by trial number. Results from the linear mixed-effects models were visualized using the *sjPlot*-package (version 2.8.7; Lüdecke, 2021).

It is essential to point out that the data have not been collected to analyze navigation performance in the first place but to assess survey knowledge for different landmark configurations. For this reason, city models were not implemented evenly regarding route lengths or intersection types which complicated the analyses for this thesis.

CHAPTER 5

Results

5.1 The Impact of Stress on Navigation Performance

Study I (time pressure):

A total of 51 participants completed all navigation tasks, 26 of them with additionally induced time pressure and 27 without time pressure. On average, they needed 266.2 seconds from the starting point of the navigation task to the destination, covering 768.2 meters. As pointed out in section 3.1.4, the resulting speed is not applicable in a real-world environment.

However, because city models were created primarily for spatial learning acquisition, the lengths of the routes differ significantly from each other, as depicted in Figure 14. The longer a route, the more time it takes even under optimal conditions to reach a destination successfully. Therefore, these average values must be interpreted with care.

A Levene's test was applied to test for homogeneity of variance for run duration across city models. It revealed that variances were similar, $F(2, 150) = 1.2$, $p = .303$, confirming the homogeneity assumption.

Figure 14 also shows the presence of upward outliers in both run duration and run distance across all city models. Downward outliers are non-existent due to the speed limit being capped at

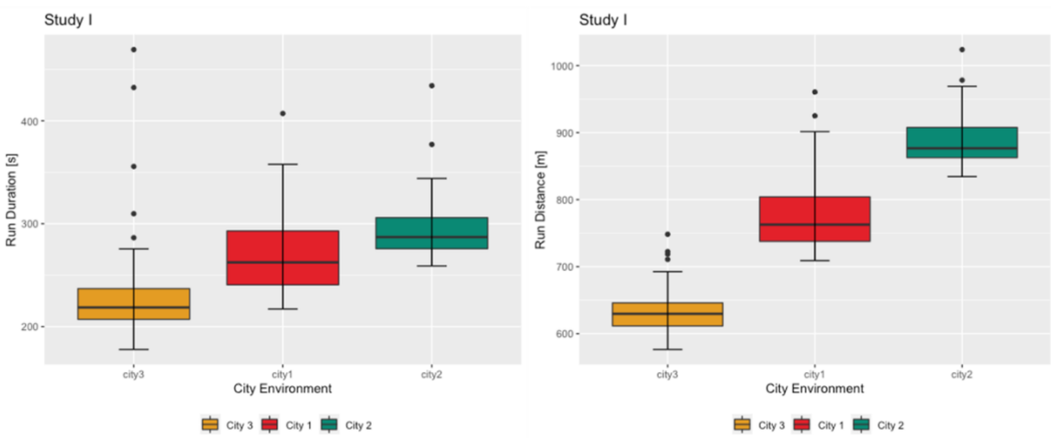


Figure 14: Boxplots depicting the differences in run duration (left) and distance (right) across the different city environments of Study I.

Environment		participantID	stress	run	landmarks	duration	is.outlier	is.extreme
Study I	city1	EREJ28	False	3	global	407.144	TRUE	FALSE
	city2	EREJ28	False	1	local	434.200	TRUE	TRUE
		ANGS8	True	1	global	377.020	TRUE	FALSE
	city3	ENRA2	False	2	global	469.239	TRUE	TRUE
		EREJ28	False	2	mixed	432.375	TRUE	TRUE
		MLEH31	False	1	mixed	355.668	TRUE	TRUE
		HDME12	False	3	global	309.713	TRUE	FALSE
		SREJ26	False	1	local	286.406	TRUE	FALSE

Figure 15: Outliers and extreme points for run duration were identified separately for every city model. It is remarkable that one participant (EREJ28) performed poorly in all three trials. Besides, all except one outlier occurred in the group without time pressure.

3.8m/s. Because ANOVAs are sensitive to outliers, especially for small sample sizes, as in our case, they were further evaluated. Therefore, outliers and extreme values were identified separately for every city model, resulting in 5 out of 51 participants being responsible for one outlier or extreme value (see Figure 15). An additional participant performed poorly across all three runs, causing one outlier and two extreme values. Since all extreme values were recorded in the no time pressure group, an exclusion of these participants would be crucial for comparing stress groups. In order not to lose any valuable data but to test the influence of extreme values on the outcome of the analysis, two ANOVAs were conducted: One ANOVA contained run durations of all three runs for all 51 participants, while the other ANOVA had runs of three participants removed being responsible for extreme values. It was found that extreme values did not have a significant impact on the main effects of the ANOVA. The following are results from the mixed factorial ANOVA including all 153 runs. Effects are reported as significant at $p < .05$.

Mauchly’s test indicated that the assumption of sphericity had been violated for the effect of city models on run duration, $W = 0.828$, $p = 0.01$, $\varepsilon = .85$. Because of both corrected values being significant, degrees of freedom were corrected using the more conservative Greenhouse-Geisser estimates of sphericity. There was a significant main effect of city environments on run duration $F(1.70, 83.58) = 63.97$, $p < .001$.

Mauchly’s test also indicated that the assumption of sphericity had been violated for the interaction of stress states and city models on run duration, $W = 0.828$, $p = 0.01$, $\varepsilon = .88$. Therefore, degrees of freedom were corrected using Huynh-Feldt estimates of sphericity. There was no significant interaction effect of stress states and city models on navigation time $F(1.76, 86.29)$

= 2.71, *p* = .079, which means that stress did not affect navigation performance differently across different cities.

There was no significant difference in run duration between the time pressure group (M = 256.84, SD = 38.93) and the no time pressure group (M = 275.93, SD = 55.36), $F(1, 49)$ = 3.84, p = .056.

	City 1			City 2			City 3			MM		
	n	M	*SD*	n	M	*SD*	n	M	*SD*	n	M	*SD*
TP	26	261.07	32.32	26	290.61	25.81	26	218.85	15.81	78	256.84	38.93
No TP	25	279.72	42.70	25	297.60	34.72	25	250.48	72.40	75	275.93	55.36
MM	51	270.21	38.56	51	294.04	30.40	51	234.36	53.81			

Figure 16: Table depicting number of observations (n), means (M), and standard deviations (SD) for run duration [s] across the different city environments for the stress group (TP), no stress group (No TP), and marginal means (MM).

Figure 17 depicts the interaction in run duration between the two stress groups and the three city models. Interestingly, time pressure had an impact on navigation performance for the shortest route (i.e., City 3). However, this advantage seemed to decrease and finally vanish with increasing run duration. This observation was confirmed by a linear mixed-effects model that assessed the influence of time pressure separately for every city model.

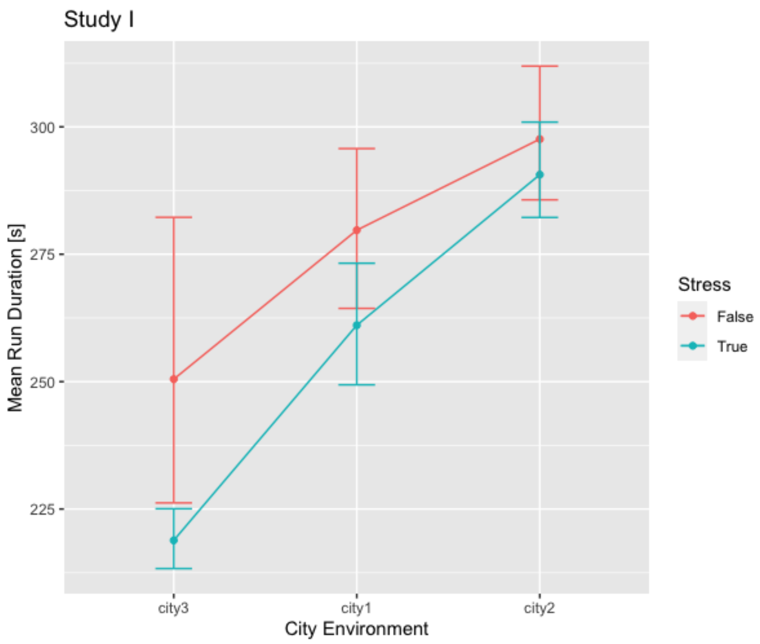


Figure 17: Graph of the interaction in run duration [s] between time pressure groups (stress) and city environments. Dots represent means and error bars depict 95% confidence intervals.

Study II (increased workload):

All 53 participants completed the navigation tasks, 27 of them concurrently performing an additional tapping task, leaving 26 participants with no induced stress factor. On average, they needed 295.8 seconds from the starting point of the navigation task to the destination, covering 847.1 meters. Again, the resulting average speed of 2.86m/s is not applicable for a walking task in a real-world environment.

Despite Credé's (2019) intentions to make both routes approximately the same length, they differed significantly (see Figure 18). These differences can be attributed not to navigators' performances but to the city models' implementation.

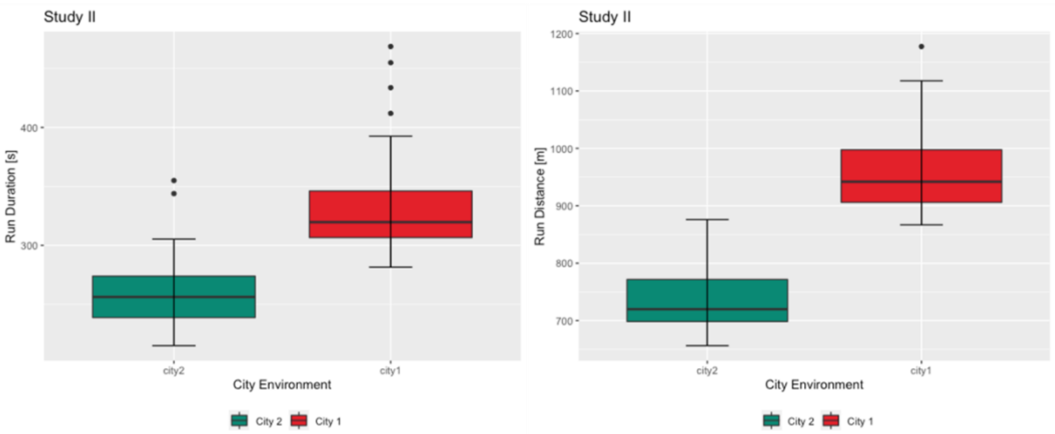


Figure 18: Boxplots depicting the differences in run duration in seconds (left) and distance in meters (right) across the two city environments of Study II.

A Levene's test testing for homogeneity of variance for run duration across the two city models revealed similar variances, $F(1, 105) = 1.06$, $p = .306$, confirming the homogeneity assumption.

Recorded outliers from Figure 18 were identified and are shown in Figure 19. Compared to Study I, the number of outliers in Study II remained constant in relation to the absolute number of trials. However, the number of extreme values dropped, decreasing the variance. It is interesting to note that all outliers in the run duration in Study II occurred in the group with additionally induced stress, therefore contradicting the findings of Study I under a different stressor. Again, one participant performed poorly in both trials, yet the impact on the ANOVA was minimal.

Environment		participantID	stress	run	landmarks	duration	is.outlier	is.extreme
Study II	city1	AAST5	True	1	global	468.629	TRUE	TRUE
		LRMD21	True	1	local	454.892	TRUE	FALSE
		NILO4	True	2	global	433.722	TRUE	FALSE
		ILCN9	True	1	local	411.918	TRUE	FALSE
	city2	NDEP1	True	1	global	355.000	TRUE	FALSE
		NILO4	True	1	local	343.905	TRUE	FALSE

Figure 19: Table showing outliers and extreme points for run duration in Study II. It is remarkable that all outliers occurred in the tapping group. One participant (NILO4) performed poorly in both trials.

There was a significant difference between the city environments on run duration $F(1, 51) = 191.30$, $p < .001$. A significant main effect was also found for run durations between the tapping group ($M = 309.71$, $SD = 57.42$) and the no tapping group ($M = 281.30$, $SD = 38.63$), $F(1, 51) = 15.39$, $p < .001$.

No significant difference was found for the interaction of stress states and city models on run duration $F(1, 51) = 2.72$, $p = .105$. This means that although run duration was affected by both stress induction and city environments, the way in which run duration was affected by the city model was not different between the tapping group and the no tapping group.

	City 1			City 2			MM		
	n	M	*SD*	n	M	*SD*	n	M	*SD*
Tap	27	350.40	47.03	27	269.02	32.73	54	309.71	57.42
No Tap	26	313.31	20.39	26	249.29	22.31	52	281.30	38.63
MM	53	332.20	40.70	53	259.34	29.56			

Figure 20: Table depicting number of observations (n), means (M), and standard deviations (SD) for run duration [s] across the two city environments for the stress group (Tap), no stress group (No Tap), and marginal means (MM).

In section 3.2, run duration was defined as being crucial for navigation performance. In order to perform well, navigators could not unintentionally deviate from the predetermined route and optimize the ratio of map retrieval to run distance. Since participants in the tapping group required significantly more time to reach the destination (+10%/+28.41s) than the group without an additionally induced stressor, the question arises as to where this difference materialized. In terms of map use, navigators in the stress group retrieved the navigational assistant significantly more often ($M = 9.22$, $SD = 3.15$) than the no stress group ($M = 6.81$, $SD = 2.36$), $F(1, 51) = 13.05$, $p < .001$. This average difference of 2.41 additional map retrievals (+35%) in the tapping

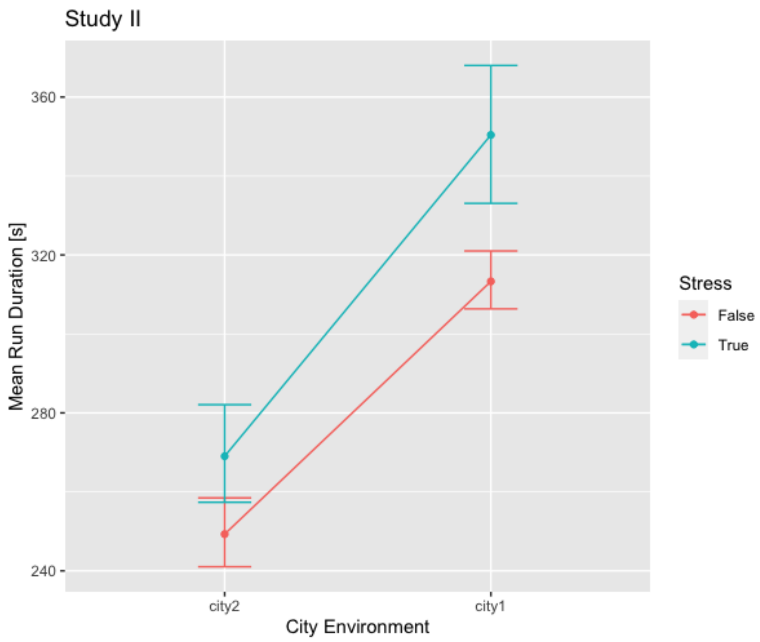


Figure 21: Graph of the interaction in run duration [s] between tapping groups (stress) and city environments. Dots are representing means and error bars depict 95% confidence intervals.

group, together with the group's average map retrieval duration (2.12s) and the three-second threshold after navigation aid consultation, resulted in an average delay of 12.37s for the tapping group. Furthermore, the occurrence of an unintended off-track event was almost doubled in the stress group (M = 0.70, SD = 0.90) compared to the no stress group (M = 0.37, SD = 0.63), $F(1, 51) = 4.86$, $p = .032$. Considering the average unintended deviation duration in the stress group of 21.31s and taking into account all decimals, another 7.21s can be attributed to the difference of run duration between the two stress groups. The remaining 8.83s cannot be reduced to a single event or behavior. Although the average number of deliberate off-track events, previously identified as beneficial for navigation performance, is also significantly different between the tapping group (M = 0.80, SD = 1.22) and the group without tapping (M = 1.77, SD = 1.80), $F(1, 51) = 6.97$, $p = .011$, their impacts on navigation performance are extremely difficult, if not impossible, to generalize.

Figure 22Figure 22 depicts the typical U- or V-shaped patterns with entry and exit points lying close together, previously seen in another city model (see Section 4.2). In contrast, various deliberate off-track lengths and patterns are visible. Building density was relatively low in this particular city model, giving navigators large open spaces for cutting corners effectively. On the other hand, other cities were much more populated, leaving almost no opportunities for effective shortcuts (see Figure 11).

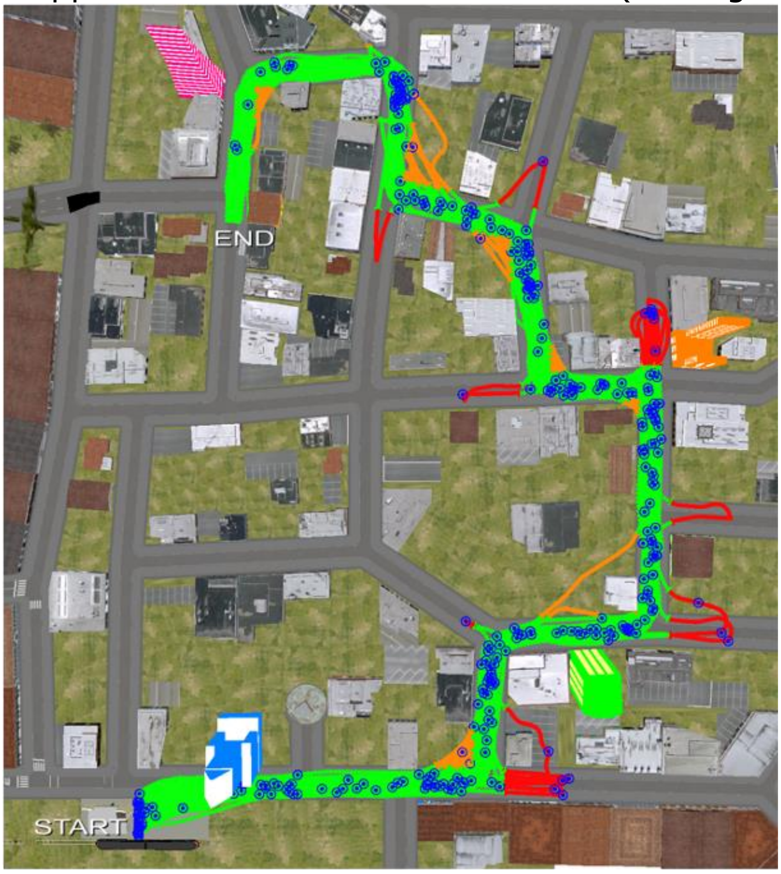


Figure 22: Bird's-eye perspective of all 53 runs conducted in the second city model of Study II. The green ribbon represents navigators' on-route nodes. Orange and red outliers depict deliberate and unintended route deviations, respectively. Blue dots stand for map retrieval locations. Please note that only global landmarks are shown in this graphic.

5.2 Learning Effect with Increasing Task Experience

Study I (time pressure):

Raw tracking data was split according to city models and trial numbers to gain an overview of mean run durations across different conditions (see Figure 23). Despite this graph not considering the repeated measures design, it provides an estimate to the extent of a potential learning effect with increasing task experience. It was found that the influence of trial numbers on run duration could not be any more diverse. While the navigation task in city model 2 was completed faster by participants with increasing task experience, run duration in city model 1 indicated the opposite. And as if that were not contradictory enough, the third city model showed a distinct increase in run duration for participants who navigated this environment in the middle of the experiment before returning to a similar level for the third trial as in the first trial.

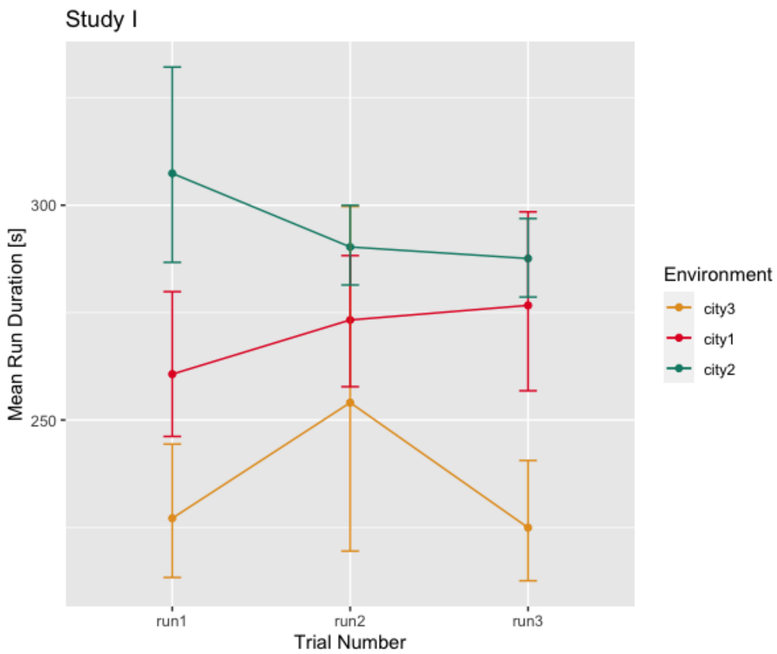


Figure 23: Graph depicting navigators' mean run duration [s] for each city model, structured by trial number.

Due to these findings, I added the stress factor directly to the linear mixed-effects model as a fixed effect to determine whether time pressure impaired a potential learning effect with increasing task experience.

No relationship was found regarding run duration between city models and trial number or between stress induction and trial number for any intercepts. It became evident, however, that the strong fluctuations in trial number were provoked by the group without time pressure (see Figure 24). The stress group, on the other hand, performed evenly across all trial numbers. Nevertheless, no learning effect was found after splitting navigators into their corresponding stress group.

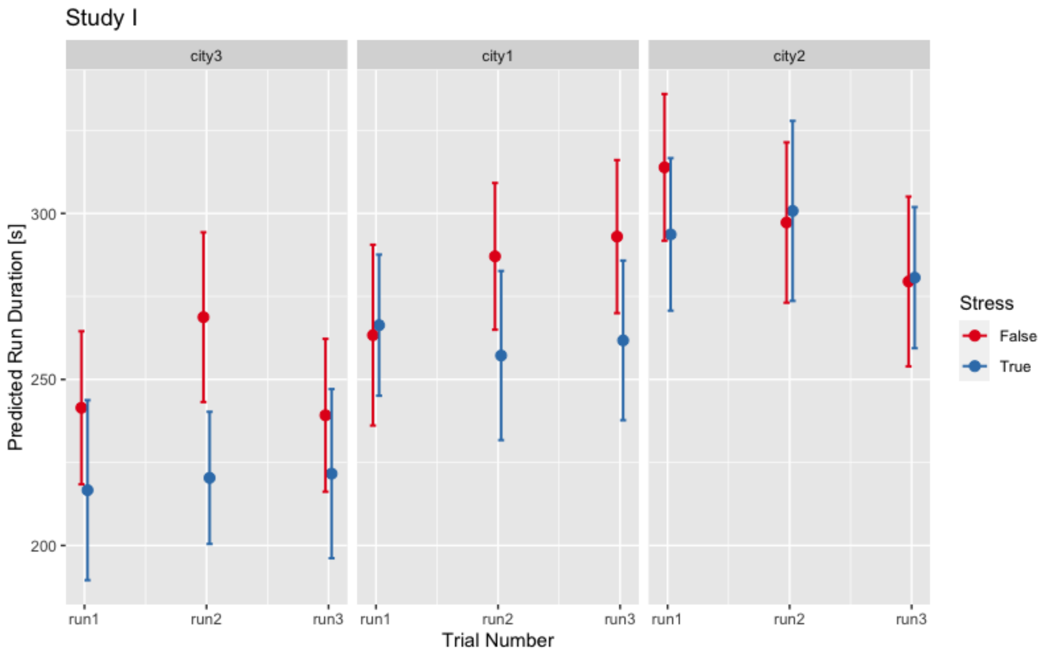


Figure 24: Linear mixed-effects model's predicted run duration [s] considering trial numbers and stress states.

By adding a second within-subject factor to the linear mixed-effects model, the absolute number of trials conducted in a specific configuration (Stress/City Model/Trial Number) was drastically reduced. The 153 total runs conducted by the 51 participants were divided into 18 different configurations (2x3x3). In addition, the dataset did not cross over, resulting in uneven numbers for different configurations (see Figure 25). These combined factors resulted in a linear mixed-effects model with low statistical power prone to outliers and extreme values. Since most outliers were located in the group without time pressure (see Figure 15), this explains the strong fluctuations in the linear mixed-effects model.

Study I | Run Configurations						
		City Model	Trial Number 1	2	3	Total
Stress	True	City 1	7	11	8	26
		City 2	6	9	11	26
		City 3	13	6	7	26
	False	City 1	10	6	9	25
		City 2	8	10	7	25
		City 3	7	9	9	25
		Total	51	51	51	153

Figure 25: Absolute number of trials listed by run configurations. Some configurations had more than double the number of trials than others.

Study II (increased workload):

For the second experiment with only two city environments, a trend was identified in run duration between the first and second trials (see Figure 26). Regardless of the city models' sequence, participants seemed to have reached the destination sooner in their second trial compared to the first trial, indicating a potential learning effect with increasing task experience.

In fact, the linear mixed-effects model verified this trend. Predicted values across both city models and irrespective of stress induction showed a reduction of 13.1s for second trials. This trend was intensified for participants performing a concurrent tapping

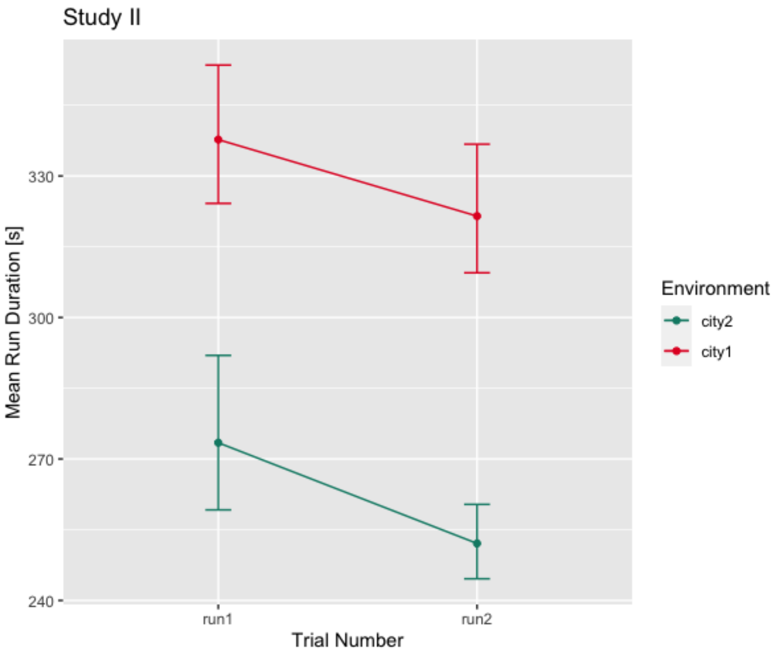


Figure 26: Graph depicting navigators' mean run duration [s] for both city models of Study II, structured by trial number.

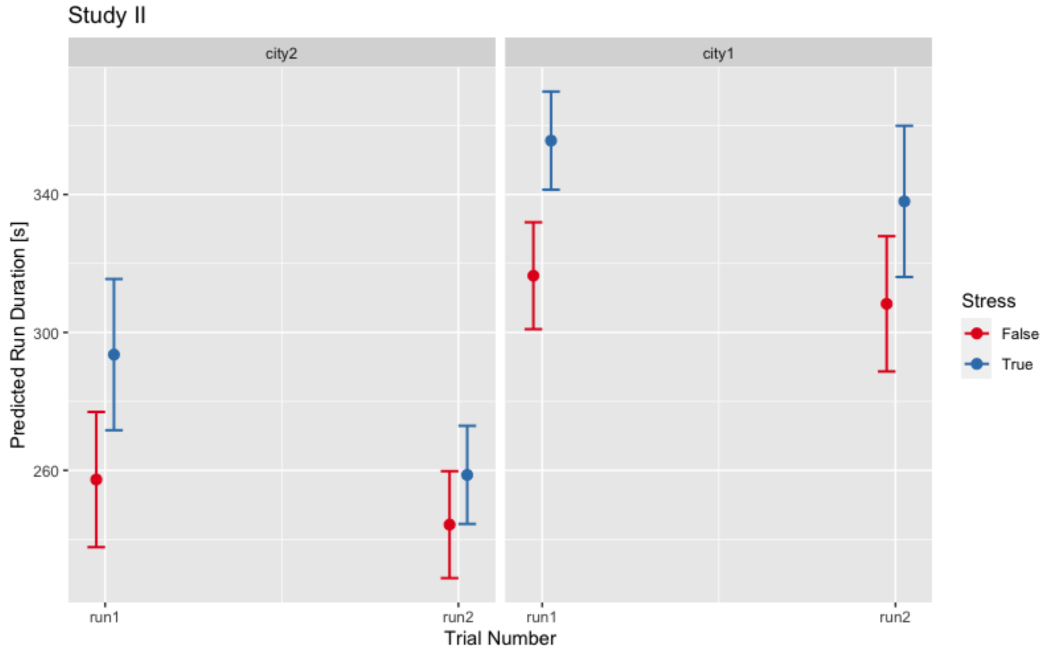


Figure 27: Linear mixed-effects model's predicted run duration [s] considering trial numbers and the presence of an additional tapping task (i.e., stress).

task, reaching the destination 21.8s sooner in the second trial. However, neither of the two effects returned significantly.

As previously seen in section 5.1, there was a significant difference in navigation performance between the two stress groups. Figure 27 shows that this groups' difference is decreasing with increasing task experience.

This linear mixed-effects model is more robust than the previous. All 53 participants conducted two trials resulting in a total of 106 individual runs. Although this absolute number of trials is almost 50% lower than in the first study, this is compensated by fewer configurations. The 2x2x2 model only had eight different configurations, which was less than half compared to Study I. As a result, not only was the number of runs higher for each configuration, but that number was also more evenly distributed, limiting the effect of large differences in navigation performance between individuals.

5.3 Unintended Route Deviations

Intersection complexity:

A total of 113 off-track events were classified into the unintended deviation category. Two of these occurred on straight path segments, far from intersections, and were therefore excluded from this analysis. Five different types of intersections with respect to route direction have been identified in section 4.3, to which the deviations were assigned. The relatively low number of 111 total recorded unintended route deviations made it necessary to combine all events across both studies.

The number of deviations per intersection type was compared to the total number of encounters to assess intersection complexity (see Figure 28). As an example, 13 T-intersections were implemented where navigators were guided to keep going straight. This type of intersection was encountered by navigators 673 times and caused 11 unintended route deviations. Given these numbers, it is expected that one in 61 participants will go astray at this type of intersection.

Intersection	Frequency	Encounters	Deviations	Expected
3S	13	673	11	61
3T	15	781	53	15
3M	11	573	9	64
4S	6	310	12	26
4T	6	310	26	12

Figure 28: Table showing at what intersection type navigators unintentionally deviated from the predetermined route. Columns from left to right: (1) intersection types according to Figure 13, (2) frequency of intersection type across all five city models, (3) numbers of encounters considering 51 (Study I) and 53 (Study II) participants, (4) number of deviations measured, (5) expected number of navigators to pass an intersection before an unintended off-track deviation occurs.

It was found that X-crossings had a much higher off-track ratio compared to T-intersections, indicating higher complexity with an increasing number of legs. At the same time, both intersection types (3T/4T) where navigators had the option to continue straight but were supposed to turn reported the largest number in absolute and relative values. These findings are in accordance with Dalton (2003), who found that navigators favor conserving linearity by walking as straight a route as possible.

Time between consecutive show-map events:

For this analysis, datasets from the two user studies were considered separately. This allowed me to investigate the effects of map section depiction modification implemented between the studies (see Section 3.1.5). In addition, map behavior between stress groups and between stress induction approaches could be analyzed. Figure 29 shows the average time between two consecutive map retrievals. In Study I, the group without additionally induced time pressure (M = 46.8, SD = 25.8) consulted the map significantly more often than the stressor group (M = 53.5, SD = 29.3), $t(555) = 2.89$, $p = .004$. In Study II, however, participants in the stress group displayed the map more frequently (M = 29.3, SD = 15.1) than participants without performing an additional spatial tapping task (M = 35.5, SD = 16.5), $t(744) = 5.30$, $p < .001$.

When comparing map intervals between the two studies, the effect of map section depiction modification from 1:106 in Study I to 1:156 in Study II becomes evident. On average, participants in the first user study with the larger map display consulted the navigation aid significantly less often (M = 49.9, SD = 27.7) than participants in the second user study with a smaller map display (M = 31.8, SD = 15.9), $t(1301) = 14.89$, $p < .001$.

These findings also go along with the linear distances between two consecutive show-map events (see Figure 30). In Study I, the distance between two consecutive show-map events was significantly higher (M = 127.0, SD = 63.5) compared to Study II (M = 84.5, SD = 42.7), $t(1301) = 14.45$, $p < .001$. Results for linear distances were also significant in both studies between the two stress groups.

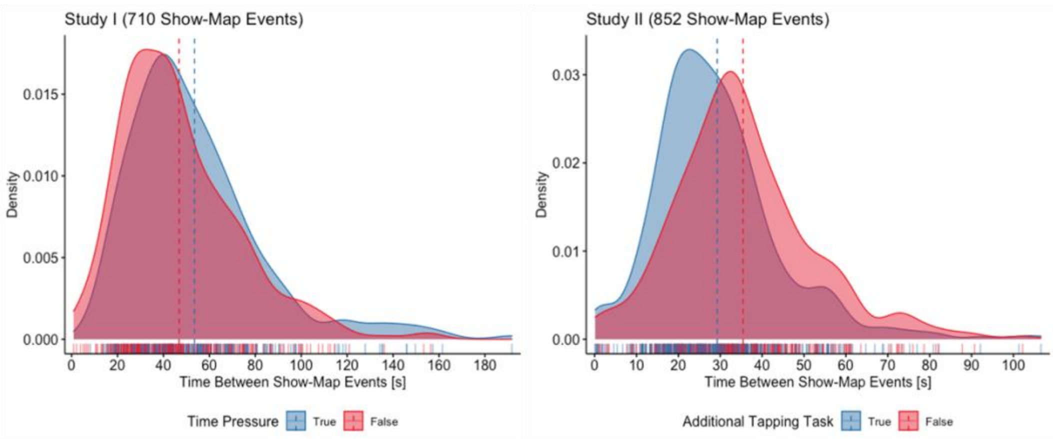


Figure 29: Density plots showing the time [s] passed between two consecutive show-map events for both user studies.

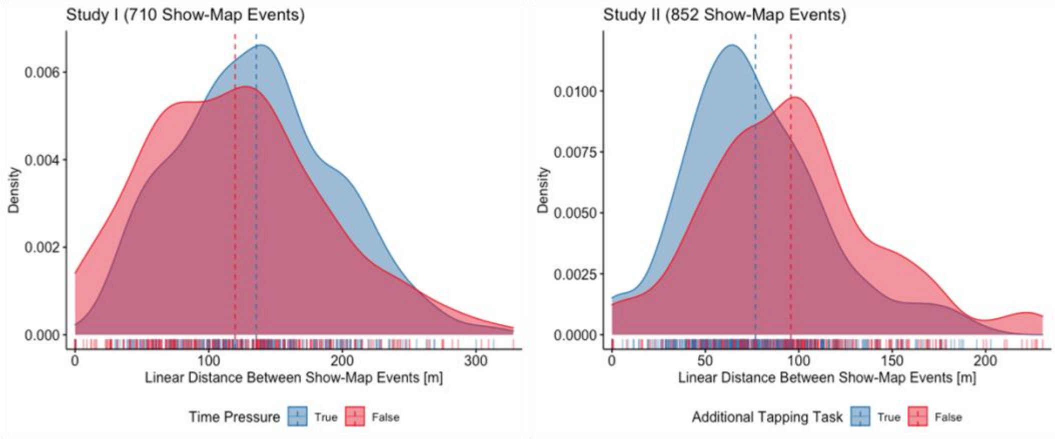


Figure 30: Density plots depicting linear distances [m] between two consecutive show-map events for both user studies.

Time between map consultation and unintended route deviation:

To evaluate if unintended route deviations were impacted by the amount of interaction between a navigator and the navigational assistant, it is necessary to know the time and linear distance to the preceding map consultation. Therefore, it was decided for this analysis to use the linear distance instead of the absolute walking distance between two events. Both time and linear distance are necessary to prevent false conclusions due to navigators standing still or moving in circles.

In Study I, participants in the no time pressure group (M = 43.1, SD = 29.8) deviated from the predetermined route sooner (see Figure 31) than participants in the time pressure group (M = 47.3, SD = 25.2). However, this difference was not significant, $t(54) = 0.56$, $p = .58$. Likewise, no significant difference was

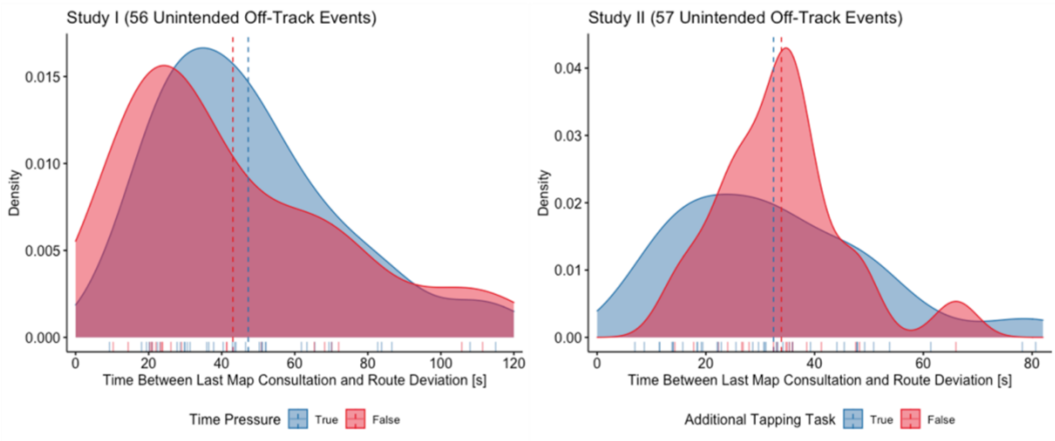


Figure 31: Density plots displaying the time [s] passed between the initiation of an unintended off-track event and the preceding map consultation for both studies.

found in Study II between the tapping group (M = 32.4, SD = 18.0) and no tapping group (M = 33.9, SD = 11.9), $t(55)$ = 0.32, p = .75.

Between the two user studies, there was a significant difference in unintended route deviations in relation to time passed since the last map consultation. Participants with the smaller map section being displayed on the front screen of the CAVE deviated significantly sooner (M = 32.9, SD = 16.1) than participants with a larger map section at hand (M = 45.8, SD = 16.8), $t(111)$ = 3.10, p = .002.

Similar to the amount of time passed between a map retrieval and an unintended deviation, the linear distance between these events is not significant between the two stress groups across both studies (see Figure 32). In Study I, navigators without time pressure on average deviated sooner (M = 109.0, SD = 76.0) than navigators with time pressure (M = 129.0, SD = 58.6), $t(54)$ = 1.13, p = .263. In Study II, the difference between the tapping group (M = 89.7, SD = 43.0) and the no tapping group (M = 96.6, SD = 36.0), $t(55)$ = 0.61, p = .547, was even smaller.

Between the two studies, a significant effect was also for the linear distance between an unintended deviation and a preceding map event. In Study I, a deviation occurred significantly further (M = 122.0, SD = 65.4) from the map retrieval location than in Study II (M = 92.0, SD = 40.6), $t(111)$ = 2.94, p = .004.

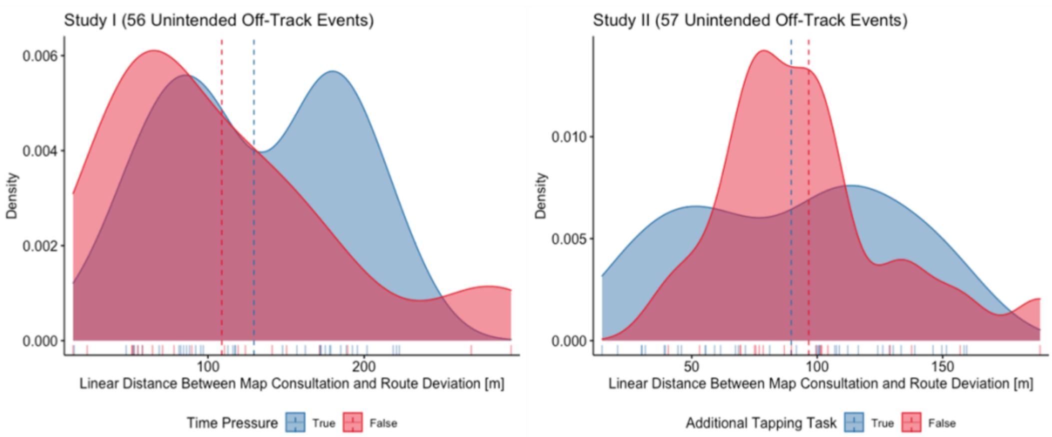


Figure 32: Density plots depicting the linear distance [m] between the starting point of an unintended route deviation and the preceding map consultation location for both studies.

To conclude, due to the map scales' modification between the two user studies, results must be viewed separately. However, the ratio of time and distance between map retrievals and route deviations remains similar across both studies.

To obtain a clear overview of the relationship in time and linear distance between two consecutive map events and a map event followed by an unintended off-track event, please refer to Figure 33. Different two-sample t-tests were conducted to test for differences between *Map::Map* and *Map::OT* events. Since they all returned not significant, it can be stated that route deviations occur at times when navigators are usually consulting the navigation aid.

	Study I				Study II			
Stress	True		False		True		False	
Unit	[s]	[m]	[s]	[m]	[s]	[m]	[s]	[m]
Map::Map	54	136	47	120	29	77	36	96
Map::OT	43	109	47	129	32	90	34	97

Figure 33: Overview of the relationship in time and distance between two consecutive map events (Map::Map) and unintended off-track deviations following map events (Map::OT).

While route deviation incidences with respect to map retrieval events do not vary between stress groups, the number of absolute deviations is significantly impacted by stress induction. A chi-square goodness of fit test revealed that the number of unintended route-following errors differed from the expected equal distribution. There was a significant difference in route deviations between the time pressure (36) and the no time pressure (20) group, $x^2(1) = 4.37$, $p = .036$ as well as between the tapping (38) and no tapping (19) group, $x^2(1) = 5.64$, $p = .018$.

Together with the findings that unintended route deviations are most likely to occur within the immediate surroundings of intersections and the fact that some intersection types tend to cause more deviations than others, there is a chance to predict imminent route-following errors. A navigational assistant being able to measure the amount of interaction from its user may prevent navigators from going astray at complex intersections if they have not been consulting the navigation aid for a certain amount of time.

CHAPTER 6

DISCUSSION & CONCLUSION

The main goal of this thesis was to assess pedestrian navigation performance under the influence of different stress induction approaches in a virtual urban environment. Therefore, navigation performance was defined as reaching a given destination as quickly as possible by executing a route-following task with the help of a track-up navigational assistant. Two datasets from separate virtual reality experiments conducted by Credé (2019) served as a basis for this work.

While performing the navigation task, regardless of stress categorization, study participants were asked to memorize relative locations of highlighted landmarks within the environment concurrently. Furthermore, they were told that the navigation task and the spatial learning task were weighted equally. In this thesis, the spatial learning task was not taken into account in order not to overlap with Credé's research.

Previous research has shown that different stress induction approaches can lead to different results of similar wayfinding tasks (Duncko et al., 2007; Klopp et al., 2012; Credé, 2019). In addition, the amount of exerted stress, as well as task complexity, have a significant impact on the level of performance (Yerkes & Dodson, 1908). Finally, individuals' reactions to stress can vary considerably (Noack et al., 2019).

This thesis provides evidence that navigation performance using a highly functional navigational assistant is affected differently under separate stress induction approaches. No global effect was found for time pressure induction. When comparing cities and their respective route lengths individually, time pressure positively influenced navigation performance for short runs. However, this effect vanished for longer runs. While time pressure did not significantly influence run duration in Study I, an opposite effect was found for Study II. Participants performing a concurrent spatial tapping task needed significantly more time to reach the destination. This finding is contradicting my expectations from the first research question.

This negative effect can be explained by the complexity of the spatial tapping task that impaired working memory in such a way that it interfered with the navigation task. The high concurrent task demand resulting from simultaneously performing a route-following task, a spatial learning acquisition task, and a tapping task led to excessive arousal in study participants. Diamond et al. (2007), referring to Yerkes & Dodson (1908), showed that a lot of combined stress could heavily influence performance. This negative effect of concurrent task demands in accord with Credé (2019), who found more deficient survey knowledge acquisition under these circumstances.

Furthermore, against my expectations, no learning effect was found with increasing task experience under time pressure. However, due to the experimental design, testing the influence of stress, city model, and trial number at once made the model very susceptible to outliers, especially for the present number of study participants. To overcome the issue of low statistical power, a larger sample size or a more uniform route length across city models would have been helpful.

In Study II, a positive effect was detected for run duration with increasing task experience. This effect was intensified for the group performing a concurrent spatial tapping task. Despite the linear mixed-effects model not returning a significant difference between trials, this p-value must be interpreted with care. Luke (2017) found that p-values are somewhat anti-conservative, especially for smaller sample sizes, crossed designs, and unbalanced datasets. All these factors apply to both datasets used in this thesis.

A vast majority of unintended off-track events were found within the immediate surroundings of intersections regarding route deviations. This finding is consistent with prior research that found decision points to be crucial for potential route-following errors (Janzen & Hawlik, 2005). Following an approach taken by Schirmer et al. (2015), five different types of intersections with respect to route direction were identified to evaluate unintended deviations further. Two major findings were generated concerning route deviations at intersections. First, navigators went astray more often at intersections with a larger number of legs, therefore confirming Richter's (2009) complexity analysis. Second, a majority of deviations occurred when navigators went straight past an intersection despite the route taking a turn. This behavioral pattern of walking as straight as possible was also found by Dalton (2003). By analyzing the pattern of periodic map retrievals, I determined that unintended route deviations were likely to occur in the same time window as the subsequent map event.

For further analyses, it would have been helpful not just to be able to reproduce participants' vista space but to track eye movement. Thus, the interaction of a navigator with the navigational assistant could have been investigated in more detail.

Reflection

I was initially planning on getting more profound insights into unintended route deviations. Therefore, this work was originally titled "Predicting imminent deviations from a predetermined route using high-resolution tracking data". When I received the dataset of the first user study, I ingenuously expected that every recorded off-track event makes up for one unintended route deviation. It was soon to be found that only 30% of these events across both user experiments could be categorized as unintended route deviations. Because this number was too small for a quantitative evaluation, I shifted my focus to navigation performance.

Bibliography

Allen, G. L. (1997). From knowledge to words to wayfinding: Issues in the production and comprehension of route directions. In Hirtle, S., Frank, A. (Eds.), *Spatial Information Theory. Lecture Notes in Computer Science, vol. 1329* (pp. 363–372). Berlin: Springer.

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

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48.

Bohonos, S., Lee, A., Malik, A., Thai, C., & Manduchi, R. (2007). Universal real-time navigational assistance (URNA) an urban bluetooth beacon for the blind. In *Proceedings of the 1st ACM SIGMOBILE international workshop on Systems and networking support for healthcare and assisted living environments (HealthNet'07)* (pp. 83–88). New York: ACM Press.

Boone, A. P. (2019). The Influence of the Human Stress Response on Navigation Strategy and Efficiency. Doctoral dissertation, University of California, Santa Barbara.

Brügger, A., Richter, K.-F., & Fabrikant, S. I. (2018). Which egocentric direction suffers from visual attention during aided wayfinding? In *3rd International Workshop on Eye Tracking for Spatial Research*, 22–27.

Brunyé, T. T., Gagnon, S. A., Gardony, A. L., Gopal, N., Holmes, A., Taylor, H. A., & Tenbrink, T. (2015). Where did it come from, where do you go? Direction sources influence navigation decisions during spatial uncertainty. *Quarterly Journal of Experimental Psychology, 68*(3), 585–607.

Brunyé, T. T., Wood, M. D., Houck, L. A., & Taylor, H. A. (2017). The path more travelled: Time pressure increases reliance on familiar route-based strategies during navigation. *Quarterly Journal of Experimental Psychology, 70*(8), 1439–1452.

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

Corona, B., & Winter, S. (2001). Guidance of car drivers and pedestrians. Department of Geoinformation, Technical University Vienna, Austria.

Credé, S. (2019). The benefits of global landmarks for spatial learning under stress. Doctoral dissertation, University of Zurich.

Credé, S., Thrash, T., Hölscher, C., & Fabrikant, S. I. (2019). The acquisition of survey knowledge for local and global landmark configurations under time pressure. *Spatial Cognition & Computation*, *19*(3), 190–219.

Credé, S., Thrash, T., Hölscher, C., & Fabrikant, S. I. (2020). The advantage of globally visible landmarks for spatial learning. *Journal of Environmental Psychology*, *67*, 101369.

Dalton, R. C. (2003). The secret is to follow your nose: Route path selection and angularity. *Environment and Behavior, 35*(1), 107–131.

Dalton, R. C., Hölscher, C., & Montello, D. R. (2019). Wayfinding as a social activity. *Frontiers in psychology, 10,* 142.

Denis, M. (2017). *Space and spatial cognition: A multidisciplinary perspective*. Abingdon, Oxfordshire: Routledge.

Diamond, D. M., Campbell, A. M., Park, C. R., Halonen, J., & Zoladz, P. R. (2007). The temporal dynamics model of emotional memory processing: A synthesis on the neurobiological basis of stress-induced amnesia, flashbulb and traumatic memories, and the Yerkes-Dodson law. *Neural plasticity, 2007*, 1–33.

Downs, R. M., & Stea, D. (1977). *Maps in minds: Reflections on cognitive mapping.* New York: Harper & Row.

Duckham, M., & Kulik, L. (2003). "Simplest" paths: Automated route selection for navigation. In W. Kuhn, M. Worboys, & S.

Timpf (Eds.), *Spatial Information Theory. Lecture Notes in Computer Science, vol. 2825* (pp. 169–185). Berlin: Springer.

Duncko, R., Cornwell, B., Cui, L., Merikangas, K. R., & Grillon, C. (2007). Acute exposure to stress improves performance in trace eyeblink conditioning and spatial learning tasks in healthy men. *Learning & Memory*, *14*(5), 329–335.

Field, A., Miles, J., & Field, Z. (2012). Discovering statistics using R. London: Sage publications.

Fink, G. (2009). Stress: Definition and history. In L. R. Squire (Ed.), *Encyclopedia of neuroscience* (pp. 549–555). Oxford: Academic Press.

Frank, A. U. (2009). Comment on "Taxonomy of Human Wayfinding Tasks" by Wiener, Büchner, and Hölscher. *Spatial Cognition & Computation, 9*(2), 166–170.

Gaisbauer, C., & Frank, A. U. (2008). Wayfinding model for pedestrian navigation. *AGILE 2008 Conference-Taking geo-information science one step further*, University of Girona, Spain.

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 & Computation, 13*(4), 319–350.

Gartner, G., Huang, H., Millonig, A., Schmidt, M., & Ortag, F. (2011). Human-centred mobile pedestrian navigation systems. *Mitteilungen der Österreichischen Geographischen Gesellschaft, 153*, 237–250.

Gillner, S., & Mallot, H. A. (1998). Navigation and acquisition of spatial knowledge in a virtual maze. *Journal of cognitive neuroscience, 10*(4), 445–463.

Golledge, R. G. (1992). Place recognition and wayfinding: Making sense of space. *Geoforum, 23*(2), 199–214.

Goodwin, M. J., Sanders, D. A., Poland, G. A., & Stott, I. J. (1997). Navigational assistance for disabled wheelchair-users. *Journal of Systems Architecture, 43*(1–5), 73–79.

Graf, C., & Schmid, F. (2010). From Visual Schematic to Tactile Schematic Maps. In S. C. Hirtle, A. Klippel, & F. Schmid (Eds.), *You Are Here 2: 2nd Workshop on Spatial Awareness and Geographic Knowledge Acquisition with Small Mobile Devices, Proceedings* (pp. 15–28). Mt. Hood / Portland, Oregon.

Heuten, W., Henze, N., Boll, S., & Pielot, M. (2008). Tactile wayfinder: A non-visual support system for wayfinding. In *Proceedings of the 5th Nordic conference on Human-computer interaction (NordiCHI'08): Building bridges* (pp. 172–181). New York: ACM Press.

Janzen, G., & Hawlik, M. (2005). Orientierung im Raum. *Zeitschrift für Psychologie / Journal of Psychology, 213*(4), 179–186.

Kassambara A. (2020a). ggpubr: 'ggplot2' Based Publication Ready Plots. R package version 0.4.0. Retrieved from https://CRAN.R-project.org/package=ggpubr

Kassambara A. (2020b). rstatix: Pipe-Friendly Framework for Basic Statistical Tests. R package version 0.6.0. Retrieved from https://CRAN.R-project.org/package=rstatix

Klippel, A. (2003). Wayfinding choremes – Conceptualizing wayfinding and route direction elements. Doctoral dissertation, University of Bremen.

Klopp, C., Garcia, C., Schulman, A. H., Ward, C. P., & Tartar, J. L. (2012). Acute social stress increases biochemical and self report markers of stress without altering spatial learning in humans. *Neuroendocrinol Lett, 33*(4), 425–30.

Kuipers, B. (2000). The spatial semantic hierarchy. *Artificial intelligence*, *119*(1-2), 191–233.

Lawrence, M. A. (2016). ez: Easy analysis and visualization of factorial experiments. R package version 4.4-0. Retrieved from https://CRAN.R-project.org/package=ez

Lobben, A. K. (2004). Tasks, strategies, and cognitive processes associated with navigational map reading: A review perspective. *The Professional Geographer*, *56*(2), 270–281.

Lovelace, K. L., Hegarty, M., & Montello, D. R. (1999). Elements of good route directions in familiar and unfamiliar environments.

In C. Freksa & D. Mark (Eds.), *Spatial Information Theory, Lecture Notes in Computer Science, vol. 1661* (pp. 65–82). Berlin: Springer.

Lüdecke, D. (2021). Sjplot: Data visualization for statistics in social science. R package version 2.8.7. Retrieved from https://CRAN.R-project.org/package=sjPlot

Luke, S. G. (2017). Evaluating significance in linear mixed-effects models in R. *Behavior research methods, 49*(4), 1494-1502.

Mark, D. M. (1986). Automated route selection for navigation. *IEEE Aerospace and Electronic Systems Magazine, 1*(9), 2–5.

Montello, D. R. (2005). Navigation. In P. Shah & A. Miyake (Eds.), *The Cambridge Handbook of Visuospatial Thinking* (pp. 257–294). Cambridge: Cambridge University Press.

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., pp. 2003–2008). London: CRC Press / Taylor & Francis.

Noack, H., Nolte, L., Nieratschker, V., Habel, U., & Derntl, B. (2019). Imaging stress: an overview of stress induction methods in the MR scanner. *Journal of Neural Transmission, 126*(9), 1187–1202.

O'Neill, M. J. (1991). Evaluation of a conceptual model of architectural legibility. *Environment and Behavior, 23*(3), 259–284.

R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.R-project.org/

Raubal, M. (2001). Human wayfinding in unfamiliar buildings: A simulation with a cognizing agent. *Cognitive Processing*, 2(3), 363–388.

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.

Richter, K.-F. (2008). Context-specific route directions. Generation of cognitively motivated wayfinding instructions, *DisKi,* vol. 314. Amsterdam: IOS Press.

Richter, K. F. (2009). Adaptable path planning in regionalized environments. In K. Stewart Hornsby, C. Claramunt, M. Denis, & G. Ligozat (Eds.), *Spatial Information Theory, vol. 5756* (pp. 453–470). Berlin: Springer.

Richter, K.-F. & Duckham, M. (2008). Simplest instructions: Finding easy-to-describe routes for navigation. In T. J. Cova, K. M. Beard, M. Goodchild, & A. U. Frank (Eds.), *Geographic Information Science. Lecture Notes in Computer Science, vol. 5266* (pp. 274–289). Berlin: Springer.

Sande, W. & Sande, C. (2013). Hello World! Computer Programming for Kids and Other Beginners (2nd ed.). Manning Publications.

Schirmer, M., Hartmann, J., Bertel, S., & Echtler, F. (2015). Shoe me the way: A shoe-based tactile interface for eyes-free urban navigation. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI'15)* (pp. 327–336). New York: ACM Press.

Schrom-Feiertag, H., Stubenschrott, M., Regal, G., Schrammel, J., & Settgast, V. (2016). Using cognitive agent-based simulation for the evaluation of indoor wayfinding systems. *arXiv preprint arXiv:1611.02459*.

Thorndyke, P. W., & Hayes-Roth, B. (1982). Differences in spatial knowledge acquired from maps and navigation. *Cognitive psychology, 14*(4), 560–589.

Tom, A. & Denis, M. (2003). Referring to landmark or street information in route directions: What difference does it make? In W. Kuhn, M. Worboys, & S. Timpf (Eds.), *Spatial Information Theory. Lecture Notes in Computer Science, vol. 2825* (pp. 362–374). Berlin: Springer.

Tomko, M. & Winter, S. (2009). Pragmatic construction of destination descriptions for urban environments. *Spatial Cognition and Computation, 9*(1), 1–29.

Van Rossum, G., & Drake Jr, F. L. (1995). Python reference manual. Amsterdam: Centrum voor Wiskunde en Informatica.

Wickham, H. (2011). ggplot2. Wiley Interdisciplinary Reviews: *Computational Statistics, 3*(2), 180–185.

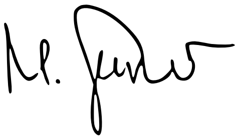
Wiener, J. M., Büchner, S. J., & Hölscher, C. (2009). Taxonomy of human wayfinding tasks: A knowledge-based approach. *Spatial Cognition & Computation*, *9*(2), 152–165.

Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology*, 18, 459–482.

Personal Declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

Flims Dorf, 30 April 2021



Matthias Saner