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Using Survival Analysis to Investigate Factors Influencing Time to Map Reactivation in Map-Assisted Pedestrian Navigation and Reactivation Time Prediction

GEO 511 Master's Thesis

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Abstract:

Mobile maps can provide efficient navigation assistance for pedestrian navigation, primarily through routes displayed on the map or auditory navigation instructions. Research on when pedestrians need navigation assistance helps mobile map navigation systems provide guidance at appropriate times. There has been research on when to give auditory navigation instructions in pedestrian navigation. However, pedestrians sometimes choose to check the route on the map rather than depend on auditory instructions due to their limitations, such as being unavailable in noisy environments. Therefore, studying when pedestrians reactivate mobile map to check the route during navigation and the factors affecting the time of map checking are significant. It can help navigation systems provide proactive and context-aware guidance according to pedestrians' needs, which can reduce pedestrians' cognitive load and improve the pedestrian navigation experience.

To achieve this goal, this thesis utilized a dataset from a map-assisted pedestrian navigation experiment in a virtual reality environment. Survival Analysis was applied for statistical analysis due to its advantage in analyzing time-to-event data. It focuses on studying how long it takes pedestrians to reactivate the mobile map to check the route after it has been locked, and the factors influencing this time.

The results demonstrate that human factors (e.g., age, spatial ability, and map use frequency) and environmental factors (e.g., route length, route section, and shortcuts) significantly impact the time to map reactivation during map-assisted pedestrian navigation. The results also illustrate the time when pedestrians need navigation instructions is predictable according to these factors by applying Survival Analysis.

Keywords: pedestrian navigation, mobile map, navigation guidance, time to map reactivation, survival analysis

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Contents

List of figures:

List of tables:

1 Introduction:

1.1 Motivation

Imagine you are traveling to an unfamiliar city. When you want to go to a highly-rated restaurant, you will most likely use a mobile map on your smartphone for navigation because mobile maps can help you navigate and orient yourself in unfamiliar cities (Delikostidis & Van Elzakker, 2009; Mantoro et al., 2012). However, sometimes you must stop and take out your mobile map to check if you are on the right route. This is a very annoying process for the navigators, especially when you are holding luggage or enjoying the scenery along the way. If the mobile map could somewhat anticipate when you need to reactivate it to check the route and provide timely guidance, this frustrating issue would be largely resolved. Therefore, it is necessary to study **when** the navigators need spatial information from the mobile navigation system.

Mobile map navigation systems are an important part of modern navigation systems, especially with the popularity of smartphones and Global Positioning System (GPS) technology. These systems use this technology to provide accurate and real-time navigation support (Tang et al., 2020). Digital mobile maps can provide multiple levels of zoom and contain various geographic information. In addition, they can also display dynamic spatial information, such as point of interest (POI) markers around the user's location, and contain navigation instructions for the next waypoint (Brata & Liang, 2020).

However, mobile map navigation systems also have their drawbacks. Reducing the ability of spatial learning is one of the problems brought by this system. GPS-based mobile navigation systems focus more on providing route guidance rather than enhancing users' understanding of the environment and spatial configuration (Münzer et al., 2012). Over-reliance on mobile map navigation systems can lead to a decline in spatial information acquisition skills (Parush et al., 2007). In addition to the impact on spatial ability, the hardware conditions of mobile devices also bring some challenges to navigation. For instance, the limited screen size of mobile devices can cause inconvenience when users need to obtain spatial information. This makes navigation more challenging through these devices. (Burigat et al., 2006). Most seriously, when using mobile map devices for navigation, people often need to shift their visual attention from the environment to the map, which can potentially lead to traffic safety issues (Calvo et al., 2014; Calvo et al., 2013; Choe et al., 2023).

To prevent individuals from shifting their attention from the environment to the map during navigation and thereby enhancing navigation safety and spatial learning ability, various research studies offer insights into potential methods and technologies that can be employed. Audio instructions, as discussed by researchers (Bharadwaj et al., 2019), are commonly employed in navigation systems to guide users to their destinations. Tactile (Eisert et al., 2013) and multimodal navigation instructions, which combine auditory and tactile displays (Calvo et al., 2013), have also been studied as being very effective.

Aside from research on the effectiveness of different navigation instruction types, there is very little research about when to provide the user with such information. Scholars gave a general conclusion about the timing of instructions: navigators will feel more comfortable if they receive navigation guidance before they reach the decision point of the route (Winter, 2003). There is currently less empirical evidence on how to determine this specific time point in mobile pedestrian navigation systems. Most mainstream mobile map applications on the market just typically offer simple threshold-based alerts (Black et al., 2017). Nevertheless, people’s needs for the time of giving navigation instructions vary based on individual and environmental factors, some of which have been studied in some research about driving (George et al., 1996).

Walking and driving differ systematically because pedestrians are not restricted by the road network (e.g., lanes, turn restrictions, one-way streets) like drivers (Gaisbauer & Frank, 2008). To verify whether findings from studies on driving can be applied to pedestrian navigation, scholars researched the time of auditory navigation instructions in the context of pedestrian navigation (Giannopoulos et al., 2017). This study showed that human factors such as age and spatial ability, as well as environmental factors like intersection types and road segment length, significantly influence when pedestrians need navigation instructions. In this study, each decision point was considered as the starting point to observe when participants would request auditory navigation instructions.

There are two large research gaps regarding when pedestrians need navigation guidance from a navigation assistance system. **Firstly, the type of navigation guidance is limited to audio.** During navigation, the navigator may choose to read the graphical route from the map instead of using audio navigation. For different modalities of navigation guidance, the navigator's expected instruction time is also different (Kray et al., 2003). **Secondly, the starting points for study when navigators need navigation guidance are limited by decision points, such as intersections**. However, navigators need navigation guidance for different motivations, such as the need for orientation, making route decisions, monitoring progress, or recognizing the destination (Carpman & Grant, 2002). Hence, simply using decision points as a reference for determining the timing of navigation instructions is insufficient to meet user needs and improve the user experience.

Hence, it is essential to take a more flexible starting point for research and a type of guidance that is more suitable for walking navigation in exploring when pedestrians need navigation guidance and what factors affect this time. The results from this can help us better understand the relationship between potential impact factors and when pedestrians need information from the mobile map. This, in turn, improves navigation systems by providing a more informed perspective on when to deliver navigation guidance. Specifically, exploring how environmental factors influence navigation behaviors when to give navigation guidance can be dynamically adjusted based on the navigator's position and environmental factors that may impact when navigators need information in the context of Location-Based Services (LBS). Similarly, by examining human factors, adaptable navigation systems can be developed that allow for personalization of the time to give navigation guidance. Moreover, in the context of GeoAI, the findings from this thesis can also provide valuable insights for feature selection in the application of various AI algorithms in pedestrian navigation.

1.2 Research goal

To address the research gaps mentioned above, this thesis chooses the **graphical navigation route** shown on the map as the modality of navigation guidance from the mobile map navigation system. It considers **each moment when the map becomes inactive** during navigation as the starting point for researching when pedestrians need navigation guidance from the map. The research goal of this thesis is to investigate the impact of human and environmental factors on the time when navigators need to reactivate the map during map-assisted navigation. Further optimize the time for the navigation system to provide navigation instruction, providing pedestrians with a better navigation experience.

To achieve this goal, several specific definitions are needed to clarify here to help subsequent research. This thesis considers every **Map Inactive Phase (MIP)** in the navigation trajectory as subjects or cohorts. **Map reactivation** is defined as an event of interest for MIP. This study will focus on observing when an event of interest occurs for each subject, in this case, when map reactivation occurs for each MIP. **Time to Map Reactivation (TMR)** is used to reflect when map reactivation occurs for each MIP. It also directly reflects when the navigators need to obtain information from the mobile map again.

1.3 Research questions and hypotheses

Based on the research goal, which seeks to explore how both human and environmental factors affect the time to map reactivation during map-assisted navigation, two key questions are proposed:

Research Question One (RQ1): Which and how do human factors influence the time to map reactivation within map-assisted navigation?

Research Question Two (RQ2): Which and how do environmental factors influence the time to map reactivation within map-assisted navigation?

To address the research questions posed above, this thesis formulates two hypotheses that reflect the expected impact of human and environmental factors on the time to map reactivation. These hypotheses are grounded based on prior research.

For human factors, in research on the timing of navigation instructions, Giannopoulos et al. (2017) found that older navigators and those with higher spatial ability tend to request auditory navigation instructions later after they pass the intersections (Giannopoulos et al., 2017). The impact of gender on navigation is multifaceted. Some researchers have noted that males tend to have strengths in certain task-space tasks that require metrics or configurations of spatial capabilities (Sargent et al., 2019; van der Ham et al., 2015). Females may have an advantage in navigational tasks that require language skills, or that use categorisation strategies (Holden et al., 2015; Piccardi et al., 2014). However, there is no explicit research on how gender affects the timing of seeking navigation guidance. Therefore, a hypothesis is proposed in this context. The dataset used in this thesis includes self-reported weekly map use frequency from participants, which could reflect the reliance on mobile maps in daily life. A study showed reliance on navigation systems could distract pedestrians' attention from the environment, which might lead to a quicker map reactivation (Parush et al., 2007). Based on these studies, hypothesis 1 was proposed.

Hypothesis One (HP1): Older navigators, females and people who use the map more frequently tend to reactivate the map more quickly. In contrast, people with higher spatial abilities tend to reactivate the map more slowly.

For environmental factors, route length has been identified as an influential factor in the timing of navigation instructions, with a negative effect (Giannopoulos et al., 2017). Pedestrians have to pay extra attention to the heavy traffic density of people and vehicles to avoid injury (Pai et al., 2019). This may lead to difficulties in remembering the navigation route, which requires a quicker map reactivation. When people choose to take shortcuts, it can increase the cognitive load (Cornell & Heth, 2000), potentially leading to quicker map reactivation to check the route. In the second half of the route, the route information navigators need to remember is less than the first half. They may reactivate the map more slowly. Regarding crossing the road, since pedestrians need to focus most of their attention on the environment while crossing, it is hypothesized that this will lead to slower map reactivation.

Hypothesis Two (HP2): Pedestrians navigating in heavy traffic density, on a longer route, in shortcuts would reactivate the map more quickly. Conversely, people walking through the second half of the route and crossing the road would reactivate the map more slowly.

2. Literature review

This chapter will review the existing research that relates to the research interest of this thesis. Based on the research questions, section 2.1 will review key concepts in pedestrian navigation. This will offer a solid foundation for understanding pedestrian navigation. Sections 2.2 and 2.3 will explore the human and environmental factors outlined in HP1 and HP2, primarily reviewing the impact of these factors on navigation performance and map use habits, which are highly relevant to the thesis's focus on time to map reactivation.

2.1 Pedestrian navigation

This section begins with a discussion of the cognitive process behind pedestrian navigation, which helps to understand how pedestrians behave during navigation from a cognitive perspective. Section 2.1.2 reviews the existing navigation assistance systems and section 2.1.3 then focuses on the map mobile map navigation, which is the interest of this study. Section 2.1.4 narrows the discussion to the content directly related to the RQ1 and RQ2.

2.1.1 Cognition in navigation

The cognitive processes underlying pedestrian navigation are complex, involving various mechanisms (see Figure 1). Understanding the cognitive processes behind navigation is important. Externalized representations such as maps or diagrams and internal representations derived from sensory experience are two basic parts of pedestrian navigation (Wolbers & Hegarty, 2010).

Externalised representations in navigation influence how individuals acquire spatial knowledge. These are presented in various forms, including maps, diagrams, verbal descriptions, etc. Research has shown that the effectiveness of these external aids depends on their accuracy and the human’s cognitive abilities. For instance, several researchers have emphasized that while external representations can help get spatial knowledge, their effectiveness is significantly affected by the accuracy of the representations (Jaeger et al., 2023). Furthermore, cognitive factors such as working memory and spatial reasoning also impact the utility of these external aids (Thoresen et al., 2016). Additionally, one study highlighted that the form in which information is presented, such as video versus direct navigation, may lead to differences in spatial knowledge acquisition (Wen et al., 2011). This indicated that the format of external representations is critical in shaping navigational outcomes.

Internal representation mainly consists of three parts: perceiving spatial information from multiple sensory cues, creating and maintaining spatial representations in different memory periods, and using and manipulating these representations to guide navigational behaviour (Wolbers & Hegarty, 2010). Perceiving spatial information relies on the integration of multiple sensory cues, which help people navigate efficiently in the environment. Various sensory modalities contribute to spatial perception, such as visual, auditory, tactile, vestibular, and others. Visual cues are probably one of the most important cues in spatial navigation because they provide rich information about the surrounding environment (Posner et al., 1976).

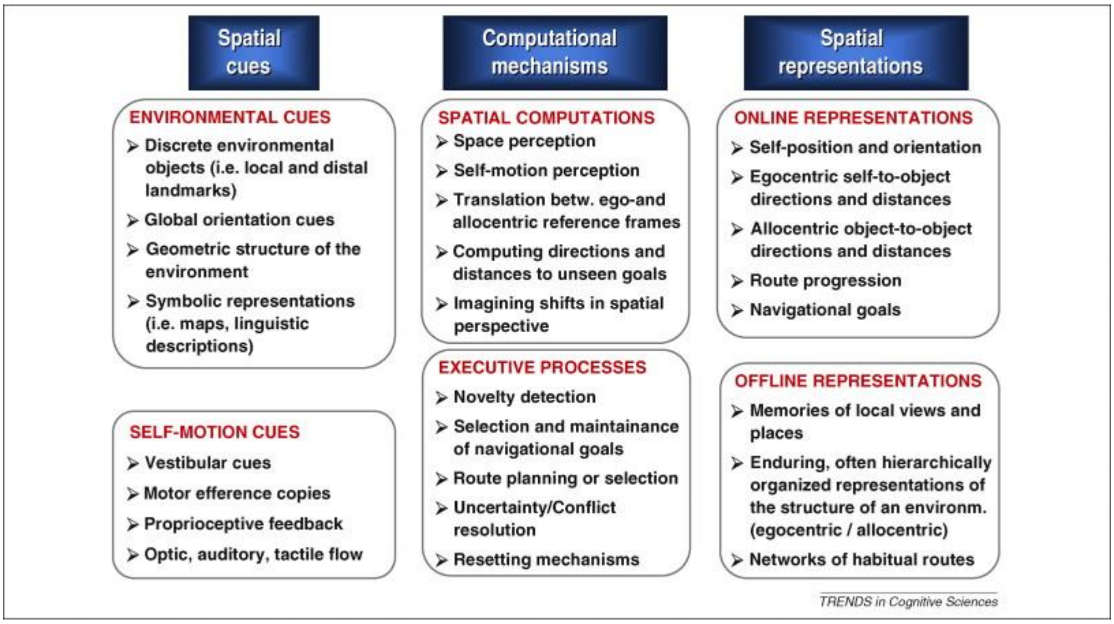

Figure 1: The complexity of spatial navigation (Wolbers & Hegarty, 2010).

Studies have shown that auditory and vibratory signals can be used to create mental spatial representations It supports the idea that spatial information can be encoded in a non-modal manner (Chebat et al., 2015). After acquiring spatial information from the outside, people create and maintain corresponding spatial representations in memory. The cognitive map plays a crucial role in this process. The ‘cognitive map’ hypothesis suggests that the brain will build a unified representation of the spatial environment to support memory and guide future navigation actions (O’Keefe & Nadel, 1978). The field of neuroscience has involved lots of research in this area, such as summarising and comparing computational cognitive models of spatial memory in navigational space (Madl et al., 2015). They also investigated exploring the impact of complicated interactions among different brain regions on cognitive mechanisms. For example, it has been studied that the hippocampus and internal olfactory cortex are integral to the formation of map-like spatial codes, while other regions (e.g., posterior pressure cortex) anchor these representations to environmental landmarks (Epstein et al., 2017). The internal spatial representation will further guide the specific behaviors of people during navigation activities. People need cognitive maps to enhance their ability to process complex environments because individuals must integrate various types of internal information as well as external information to develop an understanding of their surroundings (Silva & Martínez, 2023).

From the point of view of creating a better navigation assistance system, this article focuses more on how to better provide external spatial representations. In navigation, acquiring spatial information from an external spatial representation could be studied from two perspectives: survey perspective and route perspective (Taylor & Tversky, 1992). Reading a navigation route from a mobile map is a kind of survey perspective and navigating in the real environment can be seen as a route perspective. Maps typically show the overall layout of an environment from a survey or bird's-eye view. They are generally object-centered, maintaining a stable orientation (such as north-up), even when rotated. In contrast, people experience the environment from their first-person perspective in route perspective (Dai et al., 2018). Figure 2 illustrates an example of route perspective and survey perspective.

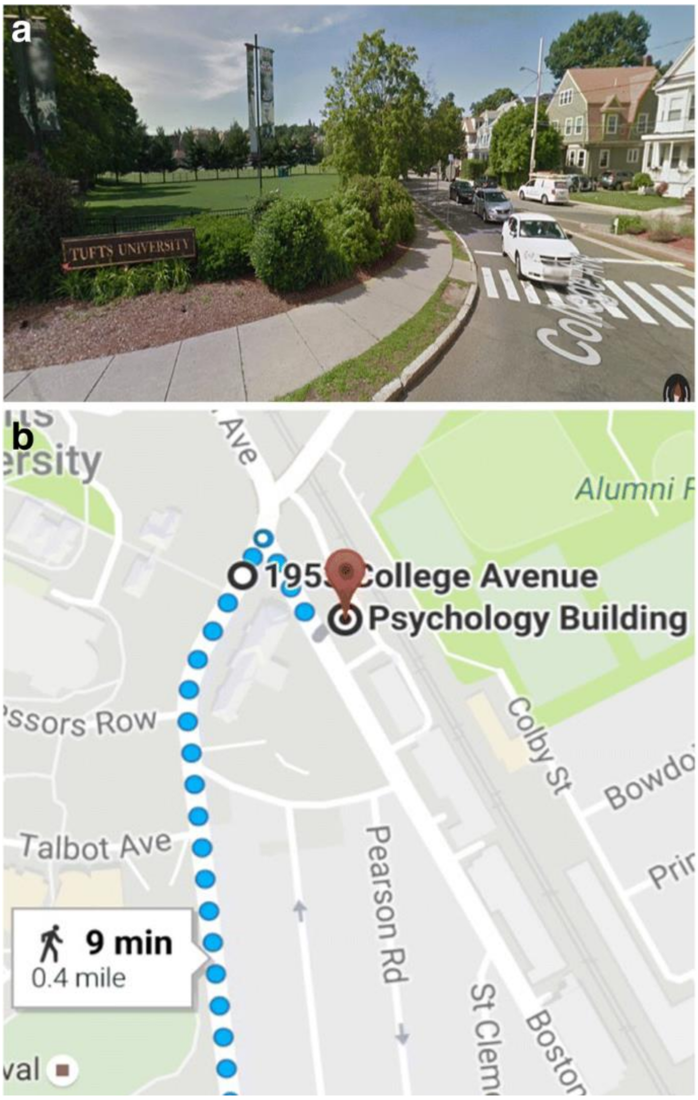

Figure 2: **a** An example of route perspective display (Google Maps, 2018a). **b** An example of survey perspective display (Google Maps, 2018b). (Dai et al., 2018)

The difference between these two different spatial perspectives has been studied by many researchers. It has been pointed out that the different perspectives affect the acquisition of spatial information (Evans & Pezdek, 1980; Sholl, 1987; Taylor et al., 1999; Thorndyke & Hayes-Roth, 1982). For example, researchers discovered that individuals who learned from maps were better at estimating overall spatial relationships and straight-line (Euclidean) distances between locations. In contrast, people who navigated the environment were more accurate in estimating local, self-to-landmark relationships and route distances (Thorndyke & Hayes-Roth, 1982). Similarly, when participants learned an unfamiliar campus building either through maps or by navigating, those who navigated in a real environment performed better on tasks involving route knowledge, while map learners excelled in tasks requiring survey knowledge (Taylor et al., 1999). These results suggest that the spatial information obtained by different spatial access modalities is different. When adopting the route perspective, people intentionally or unintentionally acquire information including the sequential arrangement of landmarks, the position of landmarks relative to the learner, and the appearance of landmarks. In contrast, when learning through a bird's-eye view perspective, people acquire information about the global, structural relationships between landmarks (Dai et al., 2018).

However, when people are faced with complex spatial environments, there is not a single but a variety of ways to obtain spatial information from the outside. Especially during navigation, switching of spatial perspectives usually occurs. For example, when navigating in an unfamiliar environment using a map, people will go through the process of acquiring spatial information through an external map, creating a cognitive map in their brain, walking in the environment based on their memory, and viewing the map again. These behaviors are repeated during a navigation process. Modern technology enables navigators to access different spatial perspectives. Pedestrians can view maps on their smartphones; drivers in unfamiliar environments may rely on GPS devices with maps (Dai et al., 2018). Scholars have investigated the combination of the two perspectives (see Figure 3) did not improve the performance of spatial learning contrasted with a single spatial perspective (Brunyé et al., 2012). In this study, perspective switching was neither forced nor directly measured. As a result, it was not possible to capture whether participants made the switch. To my best knowledge, little research is currently investigating the topic of switching between different spatial perspectives.

In this background, scholars have called for research to be conducted to examine when and where people switch perspectives, and what factors influence perspective switching (Dai et al., 2018). The research questions in this thesis are very close to this, but in the context of this thesis, the focus will be on analyzing when navigators switch from route perspective to survey perspective for navigation purposes, and what human and environmental factors affect this process.

Figure 3: The survey perspective (left) and route perspective (right) (Brunyé et al., 2012)

2.1.2 Navigation assistance systems

Based on the cognitive processes behind pedestrian navigation, various kinds of pedestrian navigation systems have been developed to meet the daily needs of pedestrian navigation. Mobile map-based navigation is one of the most dominant navigation aids. These systems utilize digital maps, GPS, inertial sensors, and other technologies to provide accurate and user-friendly navigation solutions (Brata & Liang, 2020; Kuang et al., 2018; Xu et al., 2019). The research illustrated the advantages of mobile digital maps over traditional paper maps for navigation, such as dynamic geolocation information and interactive features. These digital interfaces allow users to zoom in and out, search for points of interest (POIs), and receive turn-by-turn navigation instructions. Those features are essential for effective wayfinding in urban environments (Brata & Liang, 2020). 3D maps improve navigation by helping users better understand spatial relationships and navigate complex cityscapes by providing a more immersive navigation experience (Aditya et al., 2018). To solve the problem of unstable GPS signals, researchers have investigated the combination of inertial measurement units with other technologies, such as Bluetooth and Wi-Fi, to help pedestrian navigation by estimating parameters such as stride length and heading to achieve more accurate positioning (Kuang et al., 2018; Xu et al., 2019). With the development of artificial intelligence, machine learning techniques are also being employed to improve pedestrian navigation systems. For example, gait characteristics and machine learning algorithms are used to improve positioning accuracy. By analyzing an users' unique walking patterns, these systems can provide personalized navigational assistance (Zhou et al., 2020).

However, there are some drawbacks to mobile map navigation systems, including impacts on users' spatial abilities, navigational skills, and safety issues. A significant disadvantage of mobile map-based navigation systems is that they may impair spatial learning and cognitive mapping abilities. Research has shown that people who regularly use navigation aids have weakened basic navigational skills. They are usually unable to develop a good understanding of spatial configurations. This phenomenon is particularly worrisome for children, who may not actively interact with their surroundings while relying on such technologies (Münzer et al., 2020). Habitual GPS users tend to rely more on stimulus-response strategies than developing spatial memory strategies, which could lead to poorer cognitive mapping over time (Dahmani & Bohbot, 2020). Cheng et al. pointed that users often focus their attention on their mobile devices, which can distract them from being aware of their surroundings. This distraction may hinder their ability to process spatial information effectively (Cheng et al., 2023). More serious than the adverse effects on navigational and spatial abilities, mobile map-based navigation systems may pose immediate safety concerns for pedestrians. Because people often need to shift their visual attention from the environment to the map (Cheng et al., 2023; Giannopoulos et al., 2015), this can be very dangerous when navigating in complex environments, which in turn may lead to traffic safety issues (Calvo et al., 2013).

In recent years, researchers have tried to solve several problems of pedestrian navigation systems by developing different approaches, including auditory(Holland et al., 2002; Kuriakose et al., 2022; Zanchi et al., 2021) , vibro-tactile (Gkonos et al., 2017, 2017; Schirmer et al., 2015), augmented reality (Smith et al., 2017; Takeuchi & Perlin, 2012), and gaze-based pedestrian navigation (Giannopoulos et al., 2015). Schirmer et al. have developed a tactile navigation system (see Figure 4), which is a novel tactile interface designed for hands-free pedestrian navigation (Schirmer et al., 2015). The system is fully integrated into regular shoes without requiring permanent modifications, allowing users to navigate without diverting attention from their surroundings, enhancing navigation safety (Schirmer et al., 2015). Giannopoulos et al. introduced GazeNav, a novel gaze-based pedestrian navigation system that communicates routes based on the user's gaze at decision points. It can integrate gaze direction into navigation decisions to release visual attention (Giannopoulos et al., 2015).

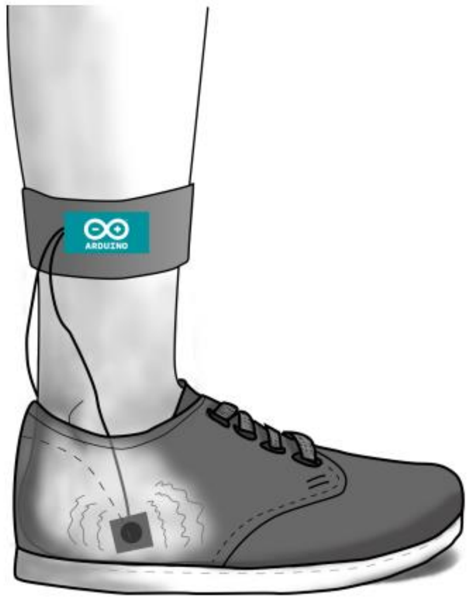

Figure 4: Overview of the Shoe me the Way components: Two vibration actuators are placed near the user’s ankle, one on either side of the foot. The actuators are controlled by a microcontroller that is worn at the lower leg (Schirmer et al., 2015).

Even though these new technologies show great potential in many areas, mobile map-based navigation systems are still the dominant navigation systems. Some researchers emphasized that the rise of smartphones had made mobile navigation applications widely accessible, allowing nearly everyone to utilize these tools for navigation (Tai et al., 2022). Therefore, alongside research into other navigation technologies, optimizing mobile map navigation aids remains important and cannot be ignored or set aside.

2.1.3 Mobile map navigation

GPS based mobile map navigation aids provide very effective help to human navigation. In the process of completing a navigation task, there are three main processes, firstly, determining one's position and the direction in which one is facing, secondly, route planning based on the destination location, and finally, executing the planned route to reach the destination (Ishikawa et al., 2008). As discussed in 2.2.1, navigators will do this throughout in navigation process, by relying on internal spatial representations from memory, or by referring to external spatial information such as maps, or both. Figure 5 describes the three main stages in the navigation process and how they relate to each other.

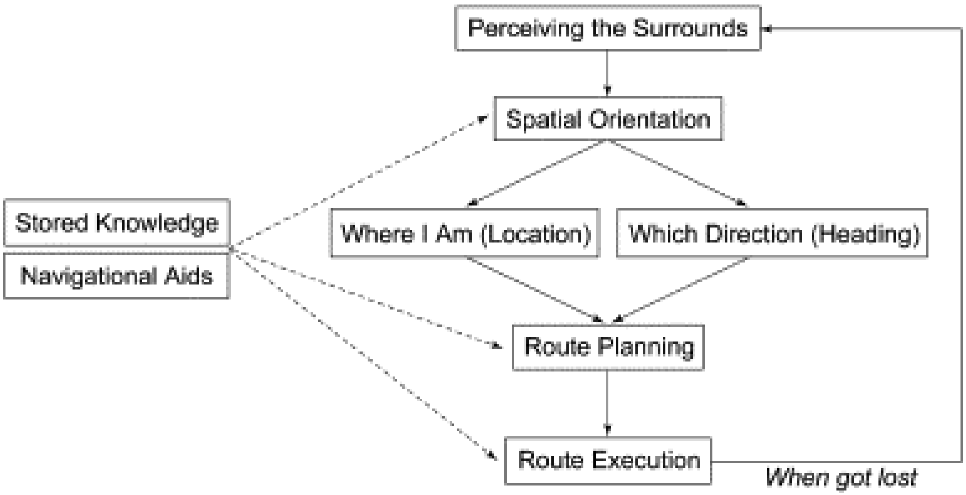

Figure 5: Schematic explanation of stages involved in navigation (Ishikawa et al., 2008).

Mobile map navigation systems play an important role in all three phases, and academics as well as designers in the industry are constantly researching how to optimize these phases.

In the spatial orientation stage, the Global Positioning System (GPS) is the core technology used by mobile maps to determine a user's spatial location. The popularity of GPS technology has changed the way users interact with mobile map applications. Scholars point out that the emergence of geographic information systems (GIS) and mobile positioning technology has promoted the widespread application of location-based services (LBS) (Luo et al., 2016). These services cover a range of functions, including navigation, location-sensitive payments, and real-time traffic updates, thereby improving the overall utility of mobile applications. The ability to access such services anytime and anywhere has become possible due to advances in high-speed cellular networks and GPS technology (Baek, 2022). However, relying on GPS for location services also brings many challenges. One of them is that smartphones consume a lot of power when using GPS. Some studies have shown that the computational demands of GPS lead to increased battery consumption, making mobile devices unable to support long-term use of LBS (Aralikatti & Anegundi, 2016). In addition, privacy issues have become a key issue in the context of LBS. Privacy-preserving techniques such as spatial hiding are essential to protect users' location data while still achieving the functionality of LBS (Shekhar et al., 2017). Striking a balance between providing personalized services and ensuring user privacy remains a key challenge in the development of mobile map applications.

The integration of a digital compass, accelerometer, and gyroscope in a mobile map navigation system plays a significant role in determining the heading direction. Digital compasses are essential sensors for determining the orientation of mobile devices. Navigation applications can provide accurate directional guidance by measuring the azimuth. Accelerometers and gyroscopes play an important role in improving navigation accuracy. The main function of the accelerometer is to measure the acceleration of the device and detect motion and changes in speed. The main function of the gyroscope is to provide information about the rotational motion of the device. This sensor combination helps mobile navigation systems compensate for the limitations of GPS (Link et al., 2013). In addition, advanced algorithms can be implemented based on the combination of these sensors to improve navigation performance. This is particularly important in pedestrian navigation because pedestrians often rely on mobile devices for real-time guidance. Zhang and Yan emphasized that pedestrian navigation systems utilize a combination of GPS, electronic compasses, and accelerometers to provide accurate and responsive navigation solutions (Zhang & Yan, 2019). However, the effectiveness of these technologies also faces some challenges. For example, the accuracy of digital compasses can be affected by environmental factors, such as magnetic interference from nearby objects. Bowers discussed the impact of compass errors on augmented reality navigation applications, emphasizing the need for powerful calibration techniques to mitigate these issues (Bowers, 2022).

Mobile maps provide navigators with many types of assistance during the route planning phase. The most important functions are route calculation and recommendation functions. Mobile maps can use different algorithms to calculate various routes from the user's current location to the destination based on the user's preferences. Dijkstra's algorithm is fundamental for finding the shortest path in a weighted graph. It systematically explores all possible paths from the starting node to the destination, ensuring that the path with the least cumulative weight is selected. Based on this algorithm, many extended algorithms have been developed, such as the A* algorithm which incorporates heuristics to improve efficiency (Zhang et al., 2023), Dynamic Routing Algorithms that adapt to indoor navigation (Link et al., 2013) and so on. In addition to recommending the shortest routes and more efficient routes that incorporate real-time traffic data (Liebig et al., 2017), researchers are beginning to explore route computation that is more responsive to people's needs, such as recommending routes that are more carbon-neutral (Zhang et al., 2023), routes with a better view of the landscape (Chen et al., 2017).

After identifying the navigation route, the display of the route on the map becomes an important topic worthy of study. Routes are typically represented as colored lines on a map. The integration of real-time data allows for dynamic route display. For example, if a user encounters traffic congestion or road closures, the application can update the route in real time and visually represent the new path on the map. This feature enhances user trust and reliance on the navigation system (Petovello, 2003). A clear user interface is essential for effective route display. Research indicates that overly complex interfaces can lead to user confusion and navigation errors (Savino et al., 2020). Therefore, mobile mapping applications strive for simplicity while providing necessary information. Because landmarks are a key element in navigation, scholars have also conducted extensive research on how landmarks are displayed on maps. It has been proposed that the inclusion of landmarks in mobile maps for pedestrian navigation could somewhat counteract the negative impact of using GPS-based navigation systems on users' spatial learning (Duckham et al., 2010; Raubal & Winter, 2002). However, the problem of how to visualize landmarks on navigation routes is a trickier one, as the depiction of landmarks on mobile maps may increase the cognitive load of the navigator (Montello, 2005). Cheng et al. noted that visualizing landmarks on maps aids users' spatial learning only when the number of displayed landmarks remains within the limits of their cognitive capacity (Cheng et al., 2022). Kapaj et al. study 3D visualization of landmarks, illustrating that different ways of visualizing landmarks have different impacts on people with different spatial abilities, and call for landmarks visualization to follow human-adaptive design guidelines (Kapaj et al., n.d.).

In the route execution phase, mobile maps offer various features that help users finish their navigation tasks successfully. One of the main features is to provide route information dynamically so that the navigators can check the navigation route anytime. There are two main ways in which mobile maps provide information in pedestrian navigation: graphic presentation of the route, or a combination of sound and vibration to provide turn-by-turn instructions. Audio turn-by-turn instructions from mobile maps can guide users at each decision point. This feature simplifies navigation by breaking down the route into manageable segments, thereby reducing cognitive load and enhancing user confidence to some extent (de Waard et al., 2017). However, there are many problems with this approach, for example, turn-by-turn navigation takes the navigator's attention away from the features of the environment, leading to distraction between the navigational aids and the environment (Gardony et al., 2013). In another aspect, audio cues may be difficult to hear in noisy urban environments, especially for pedestrian navigation (Heller et al., 2020). In this case, not all users prefer audio instructions. Some individuals may find auditory cues intrusive and may prefer visual navigation aids, such as rechecking the graphical route on the mobile map (de Waard et al., 2017). However, checking the map requires navigators to shift their visual attention from the environment to the map, which may cause safety problems (Choe et al., 2023). Scholars have made various attempts and discussions on how to address this issue, such as the use of multimodal navigation assistance systems discussed in Section 2.2.2. However, there is a lack of evidence regarding the integration of these technologies with mobile maps.

2.1.4 Time of providing navigation instructions

As can be seen from the above discussion, there has been much research on how to better provide route information for navigation. However, there has been very little research on when to provide this information, which is also very crucial to improve the user experience. If an instruction is given too early, the user might forget it by the time they reach the decision point. Conversely, if it's provided too late, the user may miss the decision point entirely or be forced to make an abrupt turn in driving navigation (Ross et al., 1997).

Current research on when to give navigation guidance has focused on the field of car navigation, which could provide some insights into the time of giving pedestrian navigation instructions. By intentionally providing drivers with navigation guidance too early or too late and asking drivers to rate the timing of the prompts after the experiment, the study identified relevant influencing factors, including the distance and time to the next junction, driving speed, and the complexity of the navigation prompt information (Ross et al., 1997). The U.S. Federal Highway Administration's general guidelines for navigation systems added weather and driver characteristics as factors that may affect navigation guidance time (Dingus et al., 1996). Age and gender as factors that may influence the optimal navigation guidance time were confirmed in subsequent empirical research (George et al., 1996), which also indicated that speed, turning patterns, and the number of cars on the street also had a significant effect.

However, it is still worth studying whether these research results based on driving navigation are applicable to pedestrian navigation. Giannopoulos et al. first proposed the issue of studying the time of giving navigation guidance in pedestrian navigation. They designed an experiment to navigate in a virtual environment to observe when pedestrian navigators requested for audio navigation instructions. Next, in order to better study time-to-event data, they applied the method of survival analysis and confirmed that human factors such as age and spatial ability, as well as environmental factors such as the type of intersection (such as T intersection, Y intersection, etc.), route length, and the degree of visualization of the intersection, would have a significant impact on the optimal voice navigation prompt time (Giannopoulos et al., 2017). Subsequently, an in-situ study was conducted to explore whether the conclusions drawn in the Virtual Reality (VR) environment can be transferred in the real environment. The researchers selected auditory, landmark-based turn-by-turn instructions as the navigation guidance modality and used each turning point as the starting point to study the navigators' most preferred navigation guidance provision time. The results show that, similar to the results of Giannopoulos et al., older people tend to get navigation instructions later. However, the difference is that people who show better global/egocentric orientation will request route instruction earlier (Golab et al., 2022). This study also added some new environmental variables such as land cover, providing a new perspective for research in this direction.

However, there are some limitations in these two main studies, also mentioned by Giannopoulos et al. (2017) and Golab et al (2021). The first one is that they both used auditory as the modality of navigation guidance. However, for different modalities of navigation instruction, the navigator's expected time is also different (Kray et al., 2003). The second is that they both use turn points as a starting point for exploring the time given to navigation. However, in pedestrian navigation, the situation is often more complex, e.g., pedestrians may look at the map several times during a route. Based on this, they also both called for future research directions to adopt a more flexible design in the modality of navigation guidance as well as the starting point for the study of preferred instruction time.

2.2 Human factors influencing navigation and map use

This section will focus on four human factors that may influence navigation and map use, including age, gender, spatial ability, and map use frequency. For each factor, it will expand the discussion from to perspective of how it influences the navigation performance and how it influences the map use strategy.

2.2.1 Age

The impact of age on navigation ability has always been a topic of great academic concern. Many research results show that as people age, various cognitive and sensorimotor functions decline, which directly affects their navigation skills. From a neurobiological perspective, neuroimaging and lesion studies have identified a network of structures involved in spatial navigation. These structures include the hippocampus, parahippocampal gyrus, cerebellum, parietal cortex, posterior cingulate gyrus, and posterior cingulate cortex (Moffat, 2009). Studies have shown that older adults have reduced or absent hippocampal activation when performing navigation tasks (Antonova et al., 2009; Meulenbroek et al., 2004). However, it has also been shown that the positive relationship between hippocampal activation and navigational performance is only reflected in younger people and not in older people (Moffat et al., 2007).

Cognitive and sensory changes associated with aging also introduce differences in the use of mobile maps. Research suggests that older users may prefer simplified interfaces to reduce cognitive load and improve usability. Renaud and Biljon highlight that Studies have shown that simplified interfaces are more popular with older users because they can effectively reduce cognitive load and improve usability (Renaud & van Biljon, 2010). As age-related differences in motivation and technology acceptance also play a crucial role in the use of mobile maps, older adults may have some difficulty in accepting new navigation assistance technologies (Cullen & Kabanda, 2018). Unfamiliarity with the technology and concerns about new tools may also hinder their use of mobile maps. Neves et al. noted that older people's use of mobile devices tends to be influenced more by functional and attitudinal factors than by physical limitations (Neves et al., 2013). The cognitive strategies adopted by different age groups also affect the use of mobile maps. The decline in spatial awareness and memory makes the elderly more likely to choose egocentric strategies, that is, to understand the surrounding environment based on their own position and perspective. However, young users do not show any difference in egocentric and allocentric (which involves understanding the environment from a more objective, map-like perspective) strategies (Rodgers et al., 2012).

In the literature investigating the effects of age on navigation performance and map use, most of the focus has been on the effects of older people, who are mostly defined as those aged 65 years or older (Hegarty et al., 2002; Ishikawa & Montello, 2006; Nazareth et al., 2019). Yu et al. pointed out this gap and studied the differences in navigation between healthy young adults (aged 18-28) and middle-aged adults (aged 43-61) (Yu et al., 2021). Their results showed that path integration abilities did not change in middle-aged adults. This provided evidence that suggests that age-related changes in navigation occur later in the aging process. In this thesis, the age difference primarily exists between the younger age groups, 18-24 and 25-33 years old. The differences in their map use strategies still require further investigation.

2.2.2 Gender

There are significant individual differences in human navigation skills, and gender may be an important influential factor. Overall, opinions are different regarding whether gender leads to differences in navigation in academia. Some studies suggested that males have advantages in certain aspects of navigation (Dabbs et al., 1998; Gagnon et al., 2018; Lawton & Kallai, 2002), while others indicate no significant gender differences (Driscoll et al., 2005; Herman et al., 1979; O’Laughlin & Brubaker, 1998). Additionally, some research shows that females may have an advantage in navigation tasks under specific conditions (Burigat & Chittaro, 2007).

Thinking back to spatial perspectives discussed in section 2.1.2, research shows that males tend to prefer Euclidean orientation strategies based on cardinal directions and distances, while females are more likely to rely on landmark-based strategies involving a series of turns and proximal cues (Dabbs et al., 1998; Lawton & Kallai, 2002). Females are more likely to be supported by the overview of the environment provided by device-assisted navigation because they are more likely to use route-based navigation strategies (Dabbs et al., 1998; Lawton & Kallai, 2002). Males demonstrate strengths in certain task-space tasks that require metrics or configurations of spatial capabilities, as well as the use of geometric information (Sargent et al., 2019; van der Ham et al., 2015). Females may have an advantage in navigational tasks that require language skills, or that use categorization strategies(Holden et al., 2015; Piccardi et al., 2014). This can partly support HP1, suggesting that females may be more likely to reactivate the map more quickly to check the graphic route for recognizing turn instructions.

Research indicates that anxiety can negatively affect the ability to encode spatial information, thereby impairing navigation performance. Women showed more spatial anxiety in certain situations (Huang & Voyer, 2017; Lawton & Kallai, 2002). Therefore, women's navigation performance may be affected in certain scenarios, such as time-constrained navigation tasks or in crowded environments. Regarding the influence of age on gender, the literature indicated that spatial representation abilities gradually mature as individuals approach puberty (Liben et al., 2013). Because the participants in this experiment were all over 18 years old, there was basically no gender effect caused by aging. Research also suggested that motivation and confidence played a crucial role in mediating gender differences in navigation performance (Schinazi et al., 2023). This finding suggested that improving motivation and confidence in women may mitigate some of the performance gaps observed in navigation tasks.

In the study to investigate the influence of gender on how navigators interact with mobile maps, researchers found that female participants spent more time in the route planning phase, which includes using mobile maps to find relevant destinations, obtain recommended routes, and memorize navigation routes (Bartling et al., 2024). However, this result cannot be directly transferred to the timing of map reactivation. On one hand, the longer time spent by females in the route planning phase may be due to their information gathering from the graphical route. On the other hand, the time invested in planning may enhance memory, reducing the need for quicker map reactivation.

2.2.3 Spatial ability

Spatial ability plays an important role in navigation, influencing how individuals perceive, interpret, and interact with the environment. Spatial ability encompasses various components, including mental rotation, perspective-taking, and spatial visualization. Research indicates that these abilities are very important during the navigation process (Allen et al., 1996; Kozhevnikov et al., 2006; Meneghetti et al., n.d.; Muffato et al., 2020). People with high spatial ability perform better in navigation. Ramanoël et al. highlighted that spatial memory and viewpoint selection abilities are important influential factors of navigational behavior (Ramanoël et al., 2020). The decline of these abilities with age may lead to navigational ability decreasing in older adults. Another study pointed out that spatial navigational decreases are influential even in the early stages of cognitive decline, underlining the importance of spatial abilities in maintaining navigational competence (Laczó et al., 2021, 2022). Furthermore, spatial abilities have been shown to be trainable. Participation in navigation tasks can lead to structural changes in the brain that enhance spatial ability (Wenger et al., 2012). This suggested that spatial navigation skills could be improved through targeted training and cognitive practice (White & Moussavi, 2016). According to the results of an empirical study by Mona et al., people with higher spatial ability completed the navigation tasks more quickly. It can be found that various studies have shown that people with higher spatial abilities perform better in navigation.

Spatial ability also has an impact on how individuals interact with and utilize maps. Navigators with higher spatial abilities tend to perform better in tasks involving map reading and navigation because they can more easily interpret spatial information and create internal representations of the environment (Kozhevnikov et al., 2006).

In addition to accessing information, spatially competent people can also better integrate visual information from maps with their existing knowledge of the environment to develop more effective navigation strategies (Boccia et al., 2017). Nevertheless, individuals with lower spatial ability may have difficulty understanding and memorizing the spatial information from maps, leading them to rely more heavily on external assistance (Dahmani & Bohbot, 2020). This partly supports HP1, because people with weaker spatial abilities rely more on the navigation route displayed on the map for assistance, leading them to reactivate the map more quickly.

The study by Giannopoulos et al. has indicated that individuals with higher spatial ability tend to request auditory navigation instructions later (Giannopoulos et al., 2017). However, in a similar experiment conducted in a real-world environment, Antonia Golab et al. reached the opposite conclusion. They found that people with better global/egocentric orientation tend to request route instructions earlier (Golab et al., 2022). This difference, as mentioned in their discussion, may be due to Antonia Golab et al. using the German-language spatial strategies questionnaire (Münzer & Hölscher, 2011), while Giannopoulos et al. employed the SBSOD (Hegarty et al., 2002). Since the data in this study also utilizes the SBSOD measure, HP1 primarily references the results from Giannopoulos et al. Results from the Mona study also indicated that participants with higher SBSOD scores had less active map use. Although the "less active map use" in this context refers to the total active/inactive time during a navigation task, it still provides some support for the

HP1 that navigators with higher spatial ability are likely to reactivate the map more slowly.

2.2.4 Map use frequency

Map use frequency is a broad concept that can refer to the frequency of map use in navigation tasks. It also can reflect the frequency of map use in daily life. In the dataset used in this study, map use frequency was based on participants' self-reported weekly mobile map use. To understand the possible influence of weekly map use frequency on TMR, it is essential to think about the motivations of map use.

The motivations for using maps in everyday life are various. The primary motivation for map use should be navigation assistance. As discussed in section 2.1.3, mobile maps provide various forms of assistance to navigators during navigation. It can assist in three key stages of navigation: spatial orientation, route planning, and route execution. Apart from the assistance in basic navigation, mobile map applications can also integrate multiple components to enhance the overall pedestrian navigation experience. Some researchers developed the Smart Pedestrian Network (SPN) model, which can provide better navigation assistance by combining urban planning, smartphone navigation apps, and commercial components to facilitate walking navigation experience (Fonseca et al., 2020). This integrated approach can not only improve route planning by taking into account pedestrians' preferences and needs but also promote physical activity and sustainable urban living. In addition, more advanced algorithms have been developed to deal with different challenges in navigation. These algorithms can optimize route planning based on various criteria, such as terrain irregularities. For instance, mobile maps can be effectively used to navigate uneven terrain, ensuring that pedestrians can select routes that are not only the shortest but also the most walkable (Yuan et al., 2017). These studies show that mobile maps can provide effective assistance to pedestrians in traditional navigation tasks. Moreover, with the application of emerging technologies, many more user-friendly navigation aids are continually being introduced.

In addition to navigation assistance, there are many other motivations for people to use maps in their lives. The other feature would be that people can get detailed information about Points of Interest (POIs) and other contextual data. Mobile maps can display dynamic geo-locative information, which includes various POIs such as restaurants, parks, and public transport stations around the user's current location (Brata & Liang, 2020). In addition, the development of big data has brought many positive impacts on mobile maps. Mobile mapping systems can enrich geographic information by integrating user-generated content. This approach allows users to contribute information about new or little-known locations, further enhancing the richness of the mapping experience (Lu & Arikawa, 2015). Many users also use mobile maps to view information about public transportation, especially when they commute on a familiar route. By integrating real-time data from public transportation schedules into mobile maps, users can get up-to-date information about arrival and departure times for buses, trains, and other public transportation(Ying et al., 2020), allowing users to dynamically adjust their travel plans(Farkas, 2016).

Based on the above discussion, weekly map use frequency does not seem to directly impact the speed of map reactivation during navigation due to the diverse purposes of map use. Additionally, map use frequency is also linked to a person's familiarity with the environment (Vaez et al., 2020). However, it can still reflect the degree of dependence on mobile maps in daily life to some extent and may influence the time of map reactivation in navigation.

2.3 Environmental factors influencing navigation and map use

There are five environmental factors will be discussed in this section. They are route length, shortcuts, spatial ability, traffic density, and road crossing. Similarly, it will also review the influence of these five factors on navigation performance and map use strategy, which will provide insights into how these environmental factors influence the time to map reactivation.

2.3.1 Route length

The length of a road has a significant impact on pedestrian navigation performance. Considered from a cognitive perspective, longer routes tend to result in an increased cognitive load because of the greater amount of information that must be received, integrated and remembered (Fu et al., 2015). The primary reason route length affects cognitive load is that longer routes typically involve more decision points, such as intersections and turns, which require additional cognitive resources for evaluation and memory retention (Krichmar & He, 2023). However, road length is only one of the factors in road complexity, and there are other factors that affect pedestrian navigation performance. Studies have shown that pedestrians often evaluate potential routes based on perceived efficiency, which includes not only physical distance but also the expected time to reach a destination (Liao et al., 2017). In addition, the built environment can significantly influence how pedestrians perceive navigation. Elements such as pavement width, the presence of trees, and overall aesthetics can affect the choice of navigation route (Ferrer et al., 2015). For instance, wide pavements and green spaces may encourage pedestrians to choose longer routes, as these features improve the overall walking experience.

Research has also shown that people may prefer longer routes with fewer obstacles. For instance, they tend to avoid slopes or uneven surfaces, even if it slightly extends their journey, as such obstacles complicate their travel (Rahaman et al., 2017; Tajgardoon & Karimi, 2015). This highlights the necessity for pedestrian navigation systems to consider not only the shortest path but also the most convenient one.

The total route length also influences how navigators use mobile maps. Because users must align their current position with the information displayed on the map, this process can consume significant cognitive resources. As a result, the design and presentation of the map play a crucial role in how effectively users navigate longer routes. Research showed that the presence of both external and internal landmarks in map descriptions significantly impacted user performance, especially as route length increases (Westerbeek & Maes, 2013). In addition, the size and scale of the map can affect how users perceive and utilize route information. Researchers have found that while map size does not significantly influence distance judgment, it does impact wayfinding performance, particularly in interactive interfaces (Chen & Li, 2020). This suggested that the physical characteristics of the map—such as its size and the level of detail provided—could influence the efficiency with which users navigate longer routes. When faced with longer routes, users may rely more on the map to maintain their sense of direction, but the complexity of the presented information might hinder their ability to do so effectively. Spatial updating is another critical aspect affected by route length. As people navigate longer distances, they must continuously update their mental representation of the environment based on the map's information (Xiao et al., 2015). This may result in navigators needing to reactivate the map more quickly to check the provided route information, which can support HP2.

2.3.2 Shortcuts

Choosing shortcuts instead of following the recommended route on a mobile map during navigation is often influenced by various factors, such as familiarity with the environment, high confidence in spatial abilities, and time constraints for completing the navigation task (Boone et al., 2019). During navigation, following a map-recommended but longer route or choosing a shortcut involves different costs and benefits. Following the recommended route requires less cognitive effort but takes more travel time. On the other hand, finding a shortcut can save travel time but introduces additional cognitive load (Lancia et al., 2023). Marchette et al.'s research in the field of neuroscience supported this point, showing that individuals who take more shortcuts exhibit greater activation in the hippocampus during spatial encoding (Marchette et al., 2011). A well-designed mobile navigation system can effectively reduce the cognitive load on navigators during the navigation process (Cheng et al., 2023; Fang et al., 2020; Zheng & Liu, 2021). From this perspective, when people choose shortcuts, they may reactivate the map more quickly to check the route again. This can partially support the HP2.

However, studies have also shown that navigators with higher spatial abilities are more likely to choose shortcuts during navigation tasks. Weisberg et al. emphasized that spatial ability is an important predictor of navigation performance, indicating that people with higher spatial skills are better at utilizing shortcuts effectively (Weisberg et al., 2014). Marchette et al. also discovered that participants who scored higher on spatial ability tests were more likely to adopt a place-learning strategy, which often involves recognizing and utilizing shortcuts (Marchette et al., 2011). This flexibility in navigation is crucial, as it allows individuals to adjust their routes based on environmental cues and previous experiences. Research suggests that people who prefer to take shortcuts rather than follow the recommended routes from mobile maps often have higher spatial abilities. The people with higher spatial abilities are less dependent on maps, as discussed in Section 2.2.3. From this perspective, it partially rejects HP2. Therefore, the impact of shortcuts on time to map reactivation during pedestrian navigation requires further data analysis to obtain more conclusive results.

2.3.3 Route section

Throughout different stages of the navigation route, the navigator's strategies and corresponding mobile map use will be different. In the early stages of navigation, pedestrians usually experience a higher cognitive load. This is mainly because they rely on external navigation aids like mobile apps and GPS devices, which require them to process a lot of information at once (Zhang et al., 2022). Interpreting maps, following directions, and staying aware of their surroundings can increase stress, especially in complex urban environments (Fang et al., 2015). In terms of behavior, early-stage navigators often exhibit caution and exploratory tendencies. They may frequently stop to reassess the route or check their devices, reflecting a lack of confidence in their spatial awareness and navigation skills (Wang et al., 2013). This behavior is often intensified by unfamiliar environments, leading to indecision during decision-making and a heavy reliance on visual cues like landmarks rather than abstract navigation instructions (Seo et al., 2016).

Cognitively, pedestrians in the later stages of navigation typically develop a stronger spatial awareness and a better understanding of their surroundings. This increased familiarity allows them to rely less on external navigation aids and more on their internal knowledge of the environment (Montuwy et al., 2019). Studies showed that as pedestrians gain experience, they become better at recognizing landmarks and using them as navigation cues, significantly improving their ability to navigate effectively (Zhu et al., 2022). This shift from relying on digital maps to understanding spatial relationships reflects deeper cognitive processing of the environment, enabling quicker decision-making and route adjustments (Ye et al., 2020). Behaviourally, pedestrians in the later stage of navigation exhibit greater confidence and fluidity in navigation. They are less likely to frequently stop and check their devices, having already formed a mental map of their surroundings to guide their route choices (Ma et al., 2024). This confidence often translates into more assured movement, allowing them to navigate crowded spaces with ease (Jiang et al., 2017). From both cognitive and behavioral perspectives, navigators in the early stages of navigation need to check the route on their mobile map more frequently, meaning they reactivate the map more quickly. However, in the later stages of navigation, as they become more confident in their understanding of the environment and navigation strategies, the need for the map decreases, leading to slower map reactivation. This aligns with HP2, which suggests that map reactivation occurs more slowly in the second half of the route.

However, researchers have identified several reasons why pedestrians may need navigation prompts. These include orientation, route decisions, monitoring progress, and recognizing the destination (Carpman & Grant, 2002). As they get closer to the destination, pedestrians may check the map more often. This is especially true in unfamiliar places or when the destination is hard to spot. They may use the map to confirm their location, leading to quicker map reactivation. This behavior differs from what is stated in Hypothesis 2, and further data analysis is required to support this.

2.3.4 Traffic density

Navigating in crowded areas presents a unique set of challenges. This has significant impacts on pedestrian behavior and safety. In heavy-density environments, the interactions between people can lead to a variety of challenges, including increased stress, changes in walking speed, and increased risk of accidents. One of the main effects of walking in crowded areas is high stress levels. Beermann's research showed that as crowd density increased, people experienced increased stress, which could lead to discomfort and anxiety (Beermann & Sieben, 2023). This stress increases when navigating through tight spaces, as people often feel their personal space is invaded. Walking speed is largely influenced by traffic density. This created unpredictable movement patterns, complicating navigation for everyone. Additionally, Wang et al. emphasized that pedestrians adjusted their walking speed based on crowd density, causing overall speed to decrease as density increases (Wang et al., 2016). The risk of accidents in crowded areas is a key concern. High-density crowds can lead to dangerous situations, especially during emergencies or moments of panic (Dias et al., 2012).

Navigating in heavy traffic density poses difficulties for pedestrians. Many studies have shown that crowded environments increase stress and cognitive load (Bilotta et al., 2018; Bitkina et al., 2019; Mavros et al., 2022). A VR navigation experiment also demonstrated that heavy traffic conditions led to higher self-reported workload and agitation among navigators (Bartling et al., 2024).

Regarding the impact of traffic density on mobile map use, Mona et al. reported no significant effect of changes in traffic density on map interaction patterns. They also found no influence of traffic density on overall map active or inactive time (Bartling et al., 2024). However, due to the stress and increased cognitive load that navigators experience in crowded environments, this thesis still hypothesizes that higher traffic density will lead to faster map reactivation.

2.3.5 Road crossing

Pedestrian road-crossing behavior is highly flexible (Gaisbauer & Frank, 2008), sometimes even not restricted by traffic rules and signals, especially on side streets or in low-traffic environments. Research shows that pedestrians make quick decisions in navigating based primarily on safety, rather than traffic rules. This especially happens when they are confident in their environment (Tom & Granié, 2011). A study on pedestrian road-crossing behavior found that pedestrians engaged in actions such as diagonal crossing and mid-block crossing on major urban roads (Papadimitriou et al., 2016).

Even though pedestrians crossing the road sometimes violate traffic rules, they need to focus more on their surroundings while crossing the road to avoid oncoming vehicles and ensure their safety. Because safety is a very important issue in pedestrian navigation (Fang et al., 2015; Schwarz et al., 2015). Some researchers have developed an app specifically to improve the safety of pedestrians crossing the road, in order to further improve the safety of pedestrians crossing the road (Wang et al., 2012). Therefore, this paper proposed in HP2 that because pedestrians need to focus more on the environment rather than on the mobile map, crossing road behavior will lead to map reactivation occurring more slowly.

3. Methods

This chapter begins by briefly outlining the experimental design of the VR study on which this thesis is based. Section 3.2 will then introduce the dataset used in the thesis, along with the methods for extracting the dependent and independent variables. Specifically, Section 3.2.2 will explain the important concept of the **censored data** within this dataset. Section 3.3 will discuss the survival analysis method used in this thesis. It is important to note that the data used in this case is part of a larger study. In this chapter, it will focus only on the experimental design, procedures, and data which is relevant to this thesis. For more detailed information about the experiment, please refer to Bartling (2024).

3.1 VR experiment

The data used in this thesis comes from a study that explored pedestrian map interaction during navigation in a virtual city. This study developed a CAVE VR system that synchronizes with a mobile map on a standard mobile phone for navigating within a virtual reality city. The experiment took place in September and October 2023 at the CAVE lab in the Department of Geography at the University of Zurich, with 54 participants in total.

3.1.1 VR urban environment

A large virtual environment (VE) was constructed using Unity (v.2021.3.24) and the "Fantastic City Generator" tool. The city included common categories of Points of Interest (POI). Some POI categories were relevant to completing the navigation tasks, such as coffee shops, restaurants, supermarkets, hotels, attractions, and kiosks. Others, like parks, sports facilities, and educational institutions, were not directly related to the tasks but kept as these POIs are typically found in a city.

The experiment created two levels of traffic density: light and heavy traffic density (see Figure 6). This was achieved by adjusting the number of vehicles, such as cars and buses, along with the number of pedestrians in the virtual environment, as well as controlling noise levels. These conditions were implemented to simulate real-world urban environments, where navigators often face varying traffic densities. For example, commercial centres and transportation hubs are usually congested during peak hours, while suburban areas tend to have lighter traffic density. This setup effectively facilitated this thesis to research when pedestrians reactivate mobile maps in navigation under different traffic conditions.

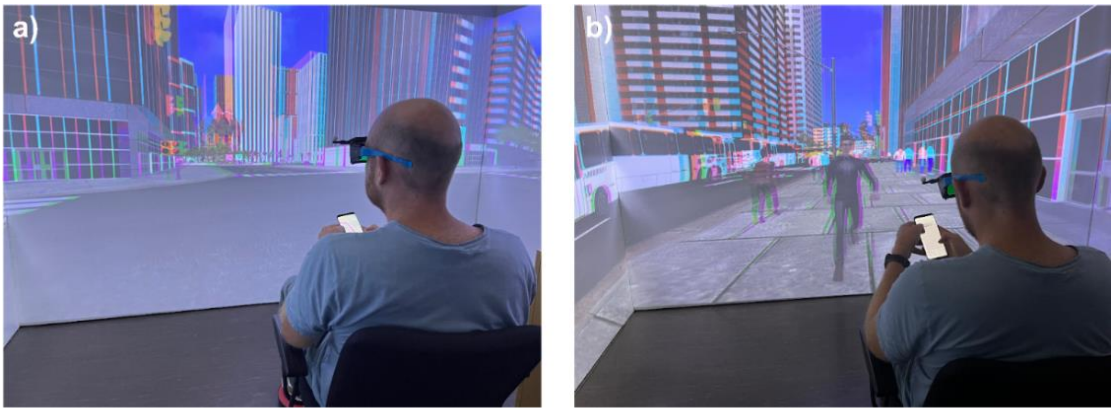

Figure 6: A participant was navigating in a) the light traffic condition with few pedestrians and vehicles and b) the heavy traffic condition with increased numbers of pedestrians and vehicles (Bartling et al., 2024)

3.1.2 Mobile map application

A mobile map was designed based on this VR urban environment. The mobile map included two versions: an adaptive version and a non-adaptive version. In the non-adaptive version, all POIs were initially displayed at 100% opacity. When participants used the search bar, the POIs matching the search query retained their full opacity, while the others were dimmed to 50%, highlighting the queried POIs. In the adaptive version, the map was simplified based on the task and the participant's location. Only task-relevant POIs were displayed, with the three closest ones shown at 100% opacity and all others at 50%. Task-irrelevant POIs, like supermarkets and restaurants, were completely removed to reduce visual complexity. The POI design was modeled based on Google Maps' symbology to align with participants' familiarity with that style. Since the primary distinction between the map versions lies in the route planning phase, this thesis mainly focuses on the pedestrian's route execution stage. In this case, the map adaptation condition is not considered within the scope of this research.

Participants used this mobile map application to complete navigation tasks within the VE. They received instructions through pop-up messages on the mobile map, providing details of the scenario’s storyline and the scenario’s task prompts. They could choose to search for their destination using the search bar. The search bar was placed at the top of the interface, allowing participants to search for their desired location (see Figure 5a). They can also directly confirm their navigation destination by observing the POI icons. Once the destination was identified, they needed to click on the destination icon and select "navigate to this place" to enable navigation mode.

After entering navigation mode, the application would automatically recommend the shortest route based on the user's current location and destination. However, it should be pointed out that the system's recommended shortest route is calculated from the main road network. There may also be other shortcuts between the starting point and the destination. In navigation mode, two new buttons would appear in the bottom right corner of the interface (see Figure 7b). The red “x” button allowed users to exit navigation mode. If participants select the wrong destination or wish to change their destination, they can use this button to exit and choose a new location. The other button, a compass icon, could center the map on the user and adjusts the orientation to match the direction they are facing. Additionally, the mobile map was configured with an **automatic screen lock** after 10 seconds of non-interaction. If the user did not interact with the map within 10 seconds, it switched to inactive mode. It would require the user to tap "unlock" on the screen to reactivate it. This design aims to closely replicate real-world navigation scenarios where mobile maps automatically lock after a period of inactivity. While the default screen lock time for iPhones is 30 seconds, the map's automatic lock was adjusted to 10 seconds in this study due to the relatively short navigation routes in the experiment.

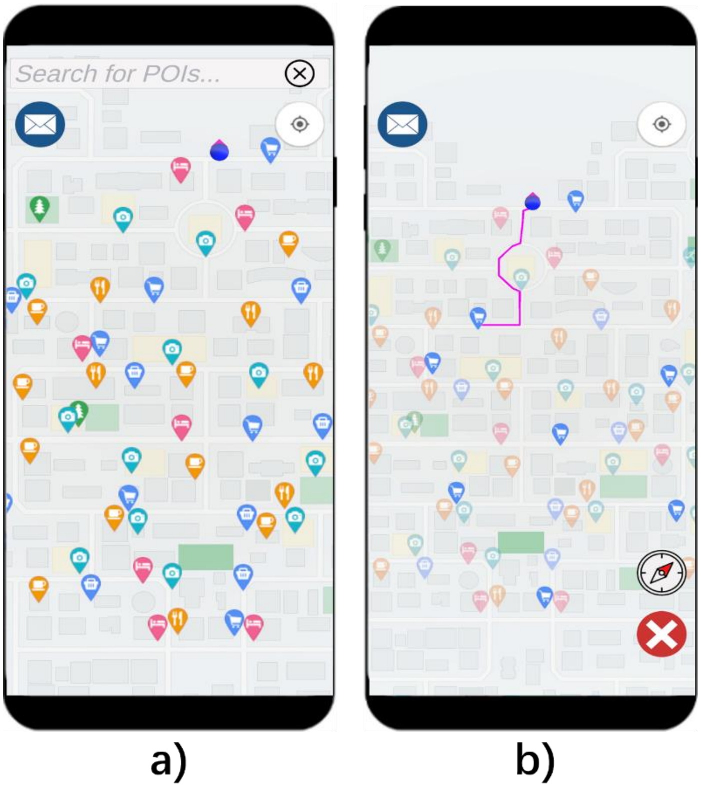

Figure 7: Mobile map interface showing a) main interface; b) navigation mode to a supermarket

3.1.3 Map-assisted navigation task

Each participant was asked to complete 16 navigation tasks, with 8 tasks conducted under heavy traffic density condition and the other 8 under light traffic density condition. The specific task information was presented to the participants via pop-up text messages on the mobile map.

It is noteworthy to mention that while the task instructions specified the category of POI that participants needed to visit, they had complete freedom to choose any specific POI belonging to that category as their destination. For example, if the task required visiting a restaurant, participants could choose any restaurant to complete the navigation task. Participants were informed that they had enough time to finish the tasks but were encouraged to complete them as efficiently as possible to ensure that they completed all conditions within a reasonable time duration.

3.2 Data preprocessing

Section 3.2.1 will first provide an overview of the dataset that will be utilized in this thesis. Section 3.2.2 will then illustrate the method to extract the dependent variable, which is the time to map reactivation in this thesis. The methods to extract the human factors and environmental factors will be discussed in section 3.2.3 and section 3.2.4.

3.2.1 Dataset overview

A total of 58 participants took part in the experiment. However, data from 4 participants could not be used because of technical issues such as VE crashes. As a result, valid data was obtained from 54 participants. Since each participant was required to complete 16 navigation tasks, there were ultimately 863 pedestrian navigation trajectories collected in this dataset (with one navigation trajectory data lost from a single participant).

The trajectory data is recorded in CSV file format, capturing a participant's position within the virtual environment (VE). The dataset includes the following parts: **time, position, rotation, task states, and map interactions**. The data is stored in point data format. The time indicates the exact time when the point was recorded, such as '2023-09-22 15:11:14.178'. The position includes ‘posX’, ‘posY’, and ‘posZ’, such as '-1260.3, 1.304999, -936.9'. Since the user's vertical position is fixed to avoid that they might ‘fly’ by some crash, ‘posY’ representing the vertical location will not be used in the data analysis. Rotation data indicates the player's direction of rotation, which is irrelevant in this case and will not be used in the analysis. For the map task state, it indicates the completion status of the navigation task, such as ' setNavigationTarget:Bricks Hotel' or 'checkedIn:Bricks Hotel’. This part is used to mark key points in the navigation route and extract the completed navigation route. Map interactions indicate the user’s interactions with the map during navigation. In this case, we mainly focus on the following two types: ‘mapLog:isScreenLocked+False’ and ‘mapLog:isScreenLocked+True’. They indicate the activation and deactivation states of the map, which will be used to determine when the mobile map entered a non-active state and when it was reactivated.

By default, the point data was recorded every 0.5 seconds. However, when changes in task state or map interactions occurred, independent records were also made outside of the default time intervals.

3.2.2 Dependent variable extraction and censored data

The dependent variable of this study is the TMR of each subject MIP, which refers to the duration from each moment when the map becomes inactive to when it is reactivated. Hence, **the subjects corresponding to TMR are not specific navigators but each map inactive phase during the navigation process**. In each navigation trajectory, the number of MIPs varies depending on the route length and the user's navigation strategies with the mobile map. Figure 8 illustrates one navigation trajectory where the participant navigated to an attraction from a coffee shop. During this navigation process, the mobile map experienced two instances of transitioning from being locked to reactivated. However, after the third map lock, the map was not reactivated again because the participant reached the destination.

This situation is referred to as **censored data.** Censored data is a critical consideration in this case. The goal of this thesis is to study the factors that influence the TMR of each MIP. Nevertheless, due to the presence of censored data, there are three map inactive phases in this navigation trajectory, but only two map reactivation events occurred. Censored data occurred because the participant reached their destination, marking the observation came to an end. For example, if the navigator arrived at their destination 10 seconds after the last map lock, even though I do not know the specific TMR, I can conclude that the time to map reactivation is greater than 10 seconds. This portion of the data still holds big value. Because it indicates that, under the existing conditions of the independent variables, the TMR is greater than a certain threshold, which is the time from the last map lock point to the destination. Discarding this data simply because we did not observe the map reactivation event would be a significant loss and could lead to biases in our experimental results. Fortunately, survival analysis provides specific methods for analyzing such data. I will discuss it in later chapters.

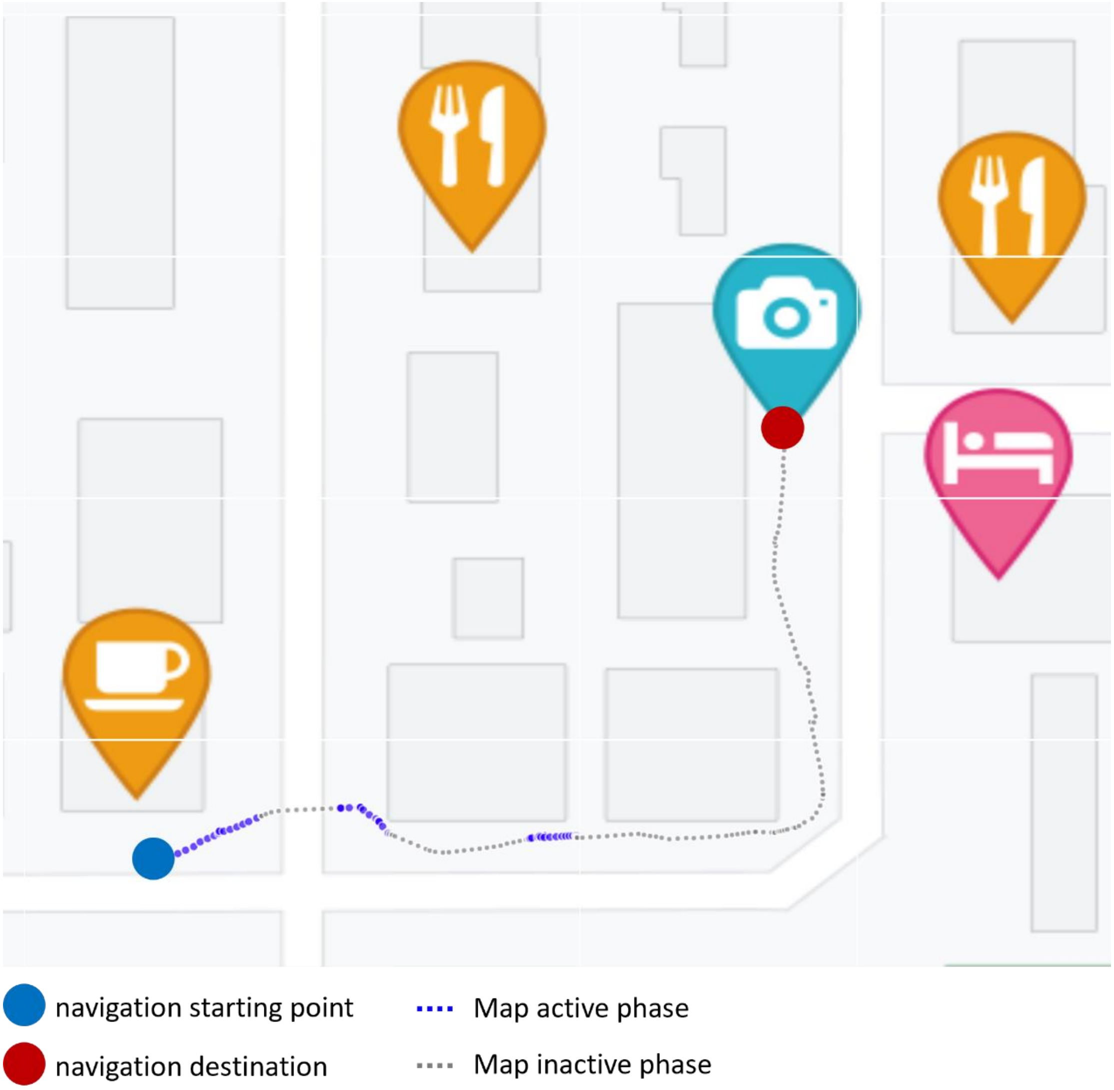

Figure 8 : This trajectory represents a participant's navigation route from a coffee shop to an attraction. After the navigation started, the mobile map remained in an active state. Before the participant crossed the street, the map was locked for the first time. After crossing, the participant reactivated the map. The map was then locked again, and after moving forward a bit, the participant chose to reactivate it once more. The map was locked for the third time and remained inactive until the task ended.

For the method to extract the dependent variable TMR, firstly I need to identify which points in the trajectory data correspond to map lock events, marking these points as starting points of that map inactive phase. This could be done by analyzing the map interactions in the dataset. If a map reactivation was observed after a map lock, it would be marked as the endpoint, and the event status of this MIP would be recorded as "occurred." The time difference between these two points represented the value of TMR. If a map lock event occurred but no map reactivation was observed before the participant reached the endpoint, the event status was marked as "censored." The time difference between the map lock point and the time of reaching the endpoint would represent the value for the censored data.

3.2.3 Human factors extraction

As mentioned in the hypothesis, **age**, **gender**, **spatial ability**, and **map use frequency** will be four human factors to be explored. These variables were collected through demographic questionnaires finished by participants before the experiment. **Age and gender** data are directly reflected in the demographic questionnaires. For **spatial ability**, I use the SBSOD scores from the SBSOD test as an indicator of spatial ability (Hegarty et al., 2002). **Map use frequency** uses the data from participants' self-reported weekly usage of mobile maps. It is categorized into three levels: "High" (four or more times a week), "Medium" (two to four times a week), and "Low" (a maximum of once per week).

3.2.4 Environmental factors extraction

For environmental variables, the thesis focuses on five key factors: **traffic density, navigation route length, route section, road crossing**, and **whether shortcuts**. Unlike human individual variables, some of these environmental factors are not directly available in the raw data and require further processing.

Traffic density is part of the experimental setup and can be directly extracted. All map reactivation events that occur under heavy traffic density are marked as 1, while those that occur under light traffic density are marked as 0.

For **navigation route length,** in each navigation route, when a point's task state was marked as ‘set navigation,’ it indicated that the participant had confirmed the destination and enabled navigation mode by clicking the destination icon. This means this participant had finished route planning and entered the route execution phase. This point will be marked as the starting point of the navigation route. Once the pedestrian checked in at the destination, the task state would display ‘check in,’ indicating that the navigation task had been completed. This point will be marked as the endpoint of the navigation route.

Since the dataset is point data, to calculate the total length of the navigation route, the Euclidean distance between each pair of consecutive points will be calculated first. The total route length then will be obtained by summing all these Euclidean distances. Each MIP will have a corresponding total length of the route to which the event belongs. (see Figure 9 as an example)

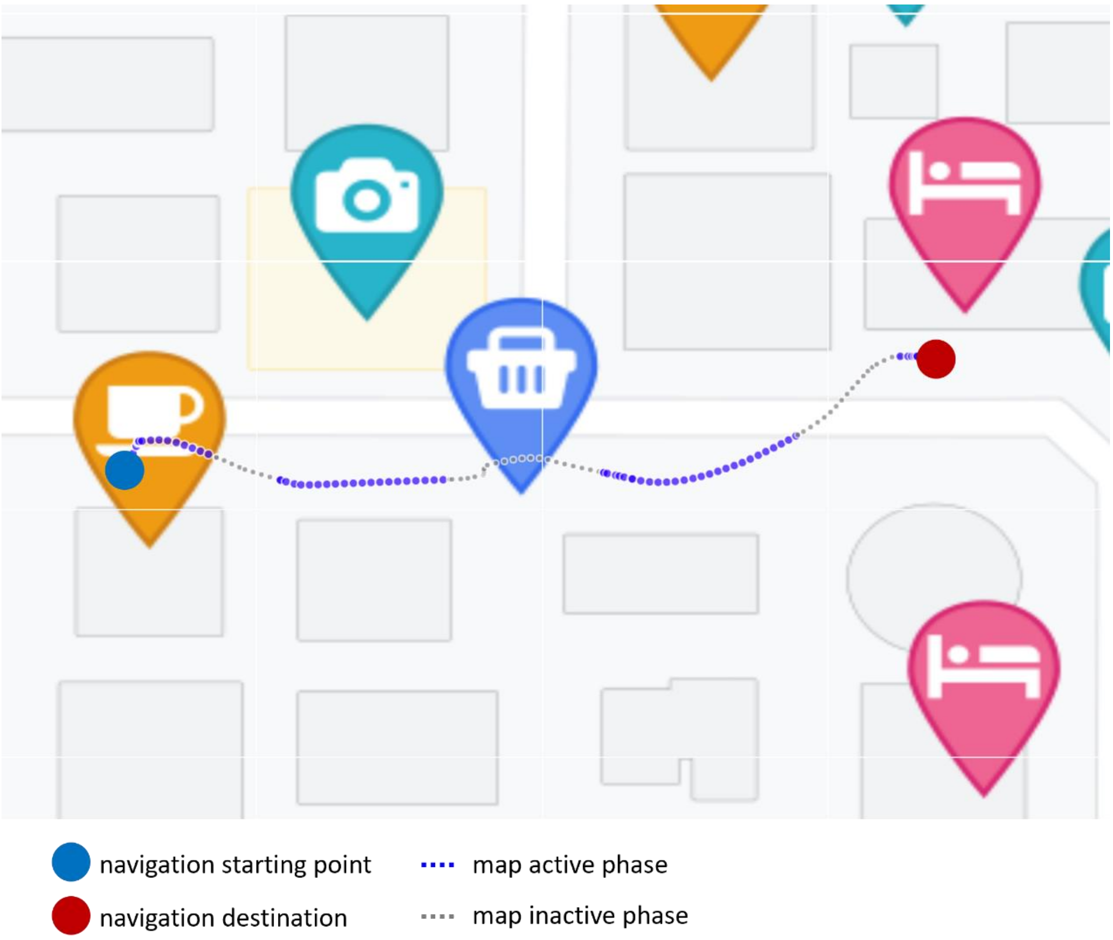

Figure 9: A navigation route with 3 MIPs occurred. These 3 MIPs has a same corresponding total length 138.5 distance units of the route.

For **route section**, I will calculate the distance from each map lock point to the starting point of the entire navigation route. This distance was then divided by the total length of the navigation route to determine the navigation completion rate for each MIP. If the navigation completion rate is below 50, the MIP will be considered occurring in the first half of the route. Conversely, if the rate is 50 or higher, the MIP will be marked occurring in the second half of the route.

To determine if there is **road crossing** during the map inactive phase, the entire traffic network was first constructed of the VE (see Figure 10). Then, I will perform spatial intersection calculations to check if there are intersections between the navigation route and the city's traffic network. If a MIP intersects with the road network, it will be marked as involving a road crossing.

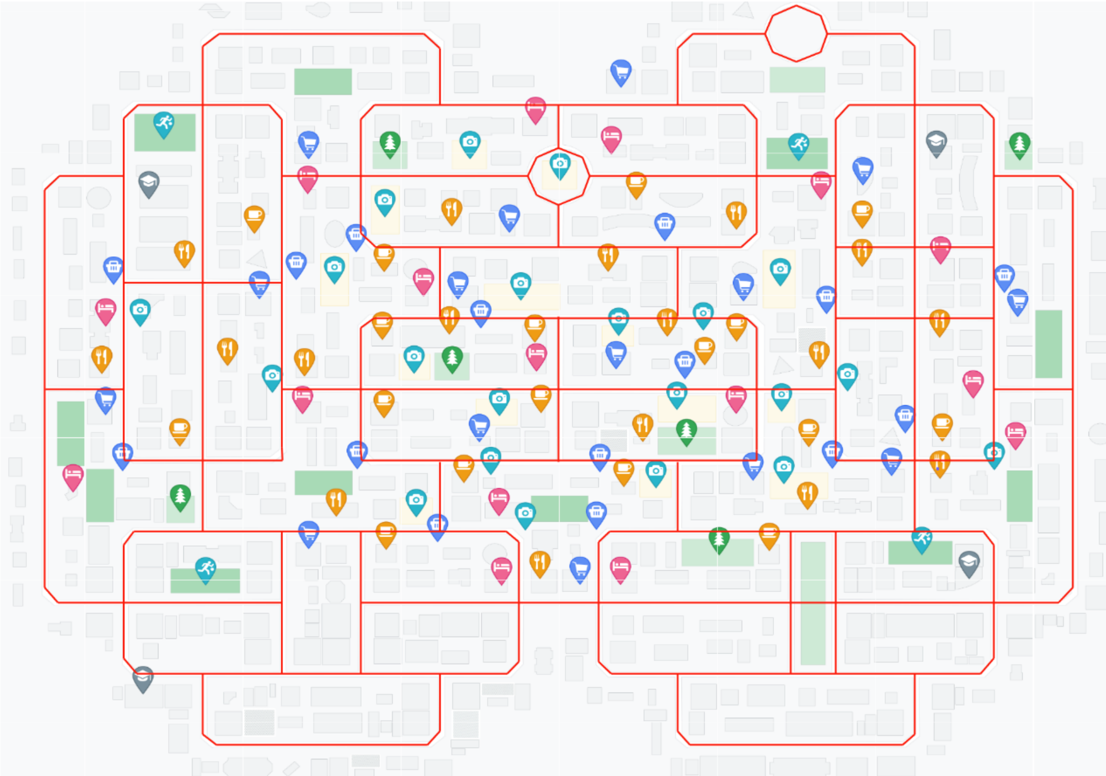

Figure 10 : The entire road network of the VE.

Regarding the variable of **shortcuts**, building blocks were first established. This factor will be detected by conducting spatial intersection calculations between navigation trajectory and the building blocks. As I mentioned in 3.1.2, the recommended navigation route provided by the mobile map is based on the main traffic network within the VE. However, participants were informed that they could freely choose whether to follow the suggested route or not. In cases where participants cut through building blocks, the navigation routes that intersected with building blocks were considered routes with shortcuts. The variable shortcuts for the MIP would be marked as 1.

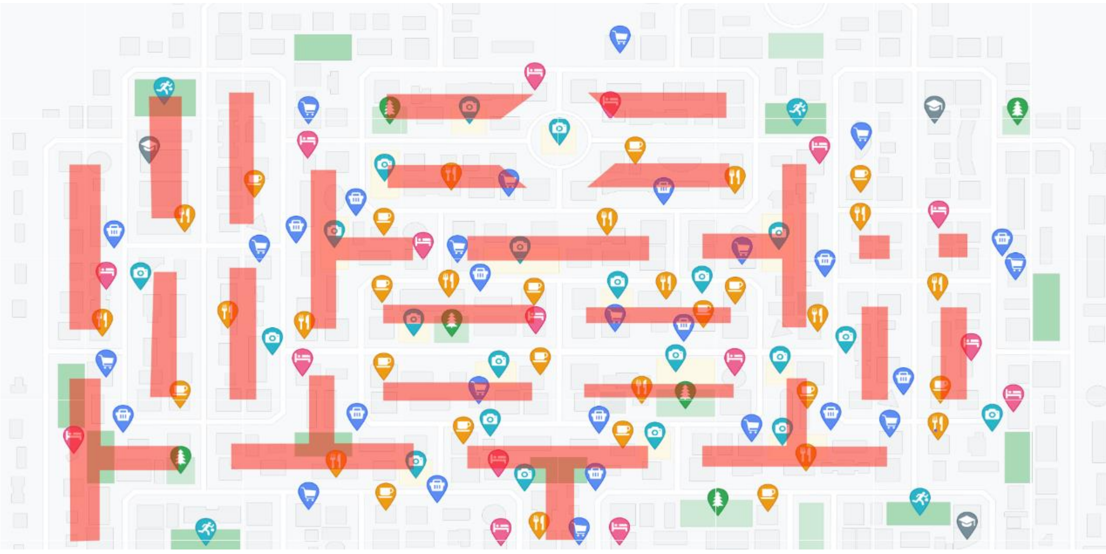

Figure 11 : The entire building blocks of the VE.

3.3 Modelling approach

After preprocessing the data and extracting the dependent and independent variables, it is crucial to find a suitable data analysis method to explore the influence of independent variables on dependent variables. Regarding the data analysis model, Section 3.3.1 will first discuss the challenges that may arise when conducting regression analysis based on the data in this case study. Following that, Section 3.3.2 will provide a basic introduction to survival analysis and explain key concepts within this methodology. Finally, Section 3.3.3 will explore which type of regression model in survival analysis is most suitable for the data analysis in this case.

3.3.1 Challenges of regression analysis

Modeling the relationship between a dependent variable and a set of independent variables is a popular interest in different research domains. It enables me to identify and quantify how changes in covariates impact the dependent variable. Undoubtedly, the most widely used approach is the family of linear regression models. However, linear regression models face several challenges, including meeting fundamental assumptions, handling censored data, addressing late entry variables, and accommodating time-varying coefficients. These issues may lead to biased estimates, loss of valuable information, and inadequate modelling of real-world phenomena. There is a need to adopt alternative approaches for more accurate data analysis.

The first challenge of utilizing linear regression models is that it should fulfill fundamental assumptions, notably the **normality of error terms** (Poole & O'Farrell, 1971). If these assumptions are violated, estimates can become biased and inconsistent. Although some studies attempt to bypass these assumptions or transform the data to fit them (Eppinga et al., 2017; Tyrrell et al., 2016), linear regression often fails with time-to-event data, which are usually skewed rather than normally distributed (Clark et al., 2003).

In our case study, **censored data** meaning the map reactivation event was not observed until the destination of the navigation route. Even though the data could not show a specific time to map reactivation, it revealed the TMR in the last map inactive phase should be greater than the time duration of last MIP. Traditional linear regression usually assumes full observation of dependent variables. Under this assumption, censored data can lead to biased regression coefficients if treated as fully observed or significant data loss if it is excluded (DiFilippo et al., 2023; Uh et al., 2008).

Additionally, some covariates, like road crossing, only become observable after the follow-up begins. These kinds of variables are defined as **late entry variables**

(Clayton & Hills, 2013). These variables must be given enough caution because analyzing these improperly can lead to huge bias. Because it is impossible to make predictions based on future covariate values (Moore, 2016c). The Stanford heart transplant study exemplifies this issue, as the initial analysis included transplant as a predictor without any processing. The results firstly showed whether accepting a heart transplant is a significant influential factor on the survival time (Clark et al., 2003). However, Gail (2008) argued that transplants should be treated in a different way because it may occur due to the long survival time. His study gave a totally converse result that the transplant did not significantly influence the survival time (GAIL, 2008).

In regression modelling, coefficients are typically constant, but independent variables can have a **time-varying effect** in many real-world phenomena. For instance, in fluid dynamics, diffusion coefficients may change over time (Wu & Berland, 2008). In this study, these dependent variables might affect TMR differently at different time points. Traditional linear regression usually fails to capture this variability, leading to inaccurate conclusions (Lu & Liang, 2006).

Furthermore, predicting results from linear regression is always an exact value. However, the exact time of giving navigation instructions cannot really meet user needs due to the complexities of navigation. Instead, it is better to predict the probability of TMR within a certain timeframe based on current conditions. This approach allows navigation systems to optimize responses according to user preferences, providing flexibility in timing for map reactivation.

3.3.2 Survival analysis introduction

In order to better address the above challenges, survival analysis will be deployed as the analysis method due to its unique advantages in analyzing time-to-event data. Survival analysis is a series of statistical methods focusing on survival time, which are follow-up times from a defined starting point to an event of interest occurs (Bewick et al., 2004). It can also be utilized to explore the factors that influence survival time (Moore, 2016a). Survival analysis is a versatile statistical methodology with applications across a wide range of domains. In fields like medicine and biostatistics, It is particularly popular in fields like medicine and biostatistics, events of interest include death, recurrence, and recovery. For instance, researchers have used survival analysis to examine survival outcomes in heart failure patients, showing that factors such as age, renal dysfunction, and blood pressure are significant risk factors for mortality in these patients (Ahmad et al., 2017). Additionally, survival analysis is also applied in many other fields. For example, in engineering, it is used to study the lifespan of equipment and optimize maintenance strategies (Ma & Bechinski, 2009). In the social sciences, survival analysis has been utilized to study various phenomena, including marriage and divorce rates (Abdel-Sater, 2022). The agricultural and ecological sciences have also benefited from survival analysis, particularly in the study of species survival and population dynamics (Ma, 2010). Moreover, survival analysis has found applications in the field of economics, where it is used to analyze time-to-event data related to economic indicators, such as the duration of unemployment spells and the factors that influence job seekers' time to reemployment (LeClere, 2005). Most relevant to this thesis is the use of survival analysis to examine the time of navigators requesting audio navigation instructions. In that research, decision points, where pedestrians need to choose among multiple available directions or paths (Tzeng & Huang, 2009), were considered as the starting points, while the event of interest was when the navigator requested navigation instructions (Giannopoulos et al., 2017).

3.3.3 Concepts in survival analysis

The **survival function** is a fundamental concept in survival analysis, which is a branch of statistics that deals with the time until an event of interest occurs. The survival function provides the probability that a subject will survive until the event of interest occurs beyond a specified time t. **In this case, the survival function will show the probability that a map inactive phase does not occur map reactivation before a certain time t**. Mathematically, it is defined as:

$$S(t) = P(T > t)$$

This function starts with a value of 1 at time 0. Obviously, all MIPs will not happen map reactivation at time 0. As time progresses, it either decreases or stays the same, but never goes below 0. Additionally, it is right continuous, meaning it doesn’t jump or change abruptly when moving from one point in time to the next. One of the most common methods for estimating the survival function is the Kaplan-Meier curves (Kaplan & Meier, 1958), which is particularly useful when dealing with censored data. The Kaplan-Meier estimator is a non-parametric statistic that provides a step function estimate of the survival function, allowing for the incorporation of censored observations without making strong parametric assumptions about the underlying survival distribution. In other words, Kaplan-Meier curves are the reflections of the observed data distribution.

Data from Participant 8 is used to illustrate the survival function. For Participant 8, there are a total of 59 MIPs records, with map reactivation events occurring 45 times and 14 censored cases. The survival function for Participant 8's MIP data is shown in Figure 12. In the survival function, the x-axis represents time, and the y-axis shows the probability that the subject is still "surviving" at the corresponding time on the x-axis. For example, at time 0, none of the MIPs have experienced a reactivation event, so the survival probability is 1. The time corresponding to a 50% survival probability is around 14 seconds, meaning there is a 50% chance that the participant will reactivate the map within 14 seconds

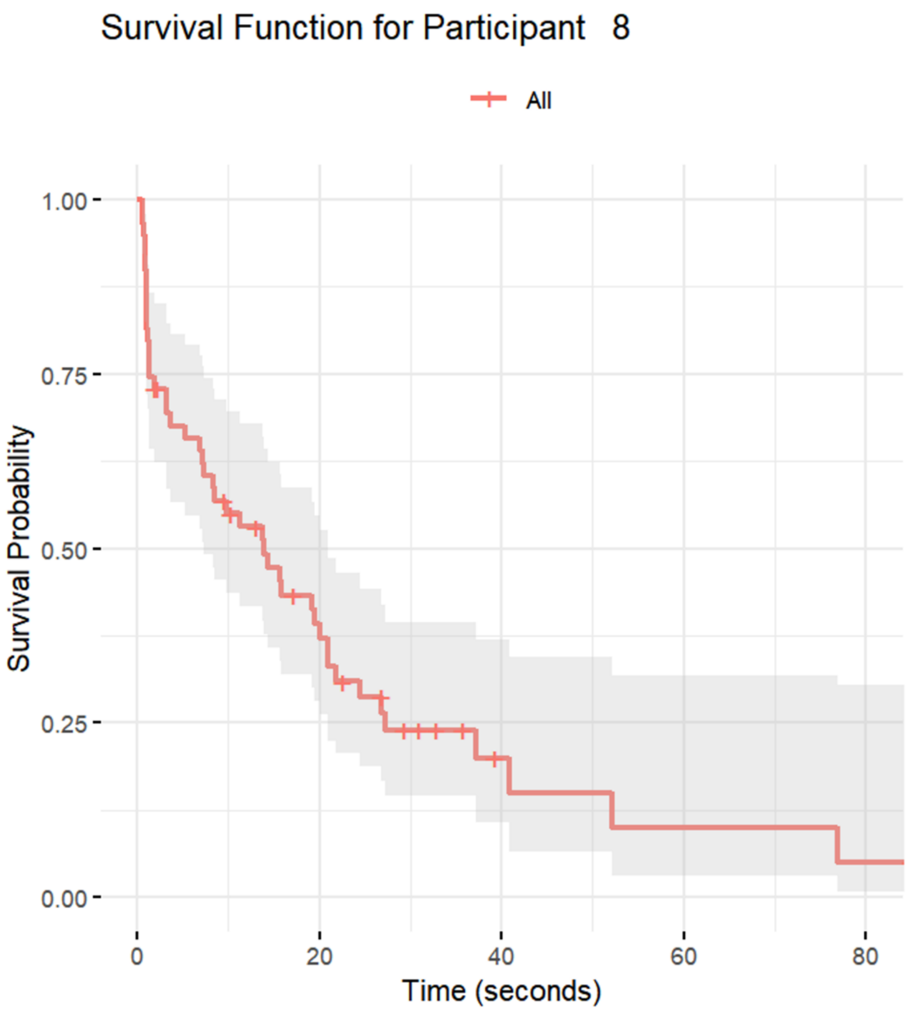

Figure 12 : Example of MIP survival function from participant 8.

The survival function is one of the most important concepts in survival analysis and also one of the key outputs of regression analysis. As a predictive result of regression models, the survival function effectively addresses the output limitations of traditional linear models. After fitting a regression model, it can generate the survival function corresponding to specific values of the covariates by inputting those values. Furthermore, based on the survival function, navigation assistance system can be set a criteria according to user’s preference, such as using the median survival time to provide route instructions to navigators.

The **hazard function** is another critical concept in survival analysis, representing the instantaneous risk of an event occurring at a specific time, given that the subject has survived up to that time (Moore, 2016a). The concept of the hazard function is used to describe the relative probability that a subject who/which has survived up to a certain time point will continue to survive to the next time point. Formally, given that a subject has already survived up to time t, the hazard function $h(t)$ may be expressed as:

$$h(t) = \lim_{\Delta t \to 0} \left(\frac{P(t < T \leq t + \Delta t \mid T > t)}{\Delta t} \right)$$

The hazard function and the survival function are mathematically related and can be derived from one another. Let us denote the time from the point where mobile map was locked (in analogy to the time-to-event concept) as t, having a cumulative distribution function T such as $F(t) = Pr(T \leq t)$, and survival function $S(t)$. It is clear that there is $S(t) = 1 - F(t)$. Hazard function, which is the probability of a process ending at point t, given that it has lasted up to that point, can be also defined as:

$$h(t) = \frac{f(t)}{S(t)}$$

Next, I will use an extreme simulation case to illustrate the relationships between the survival function, hazard function, cumulative distribution function (CDF), and probability density function (PDF) (Clark et al., 2003). Suppose the map inactive phase is reactivated uniformly within a 20-second observation window. The survival function, hazard function, CDF, and PDF are shown in Figure 13:

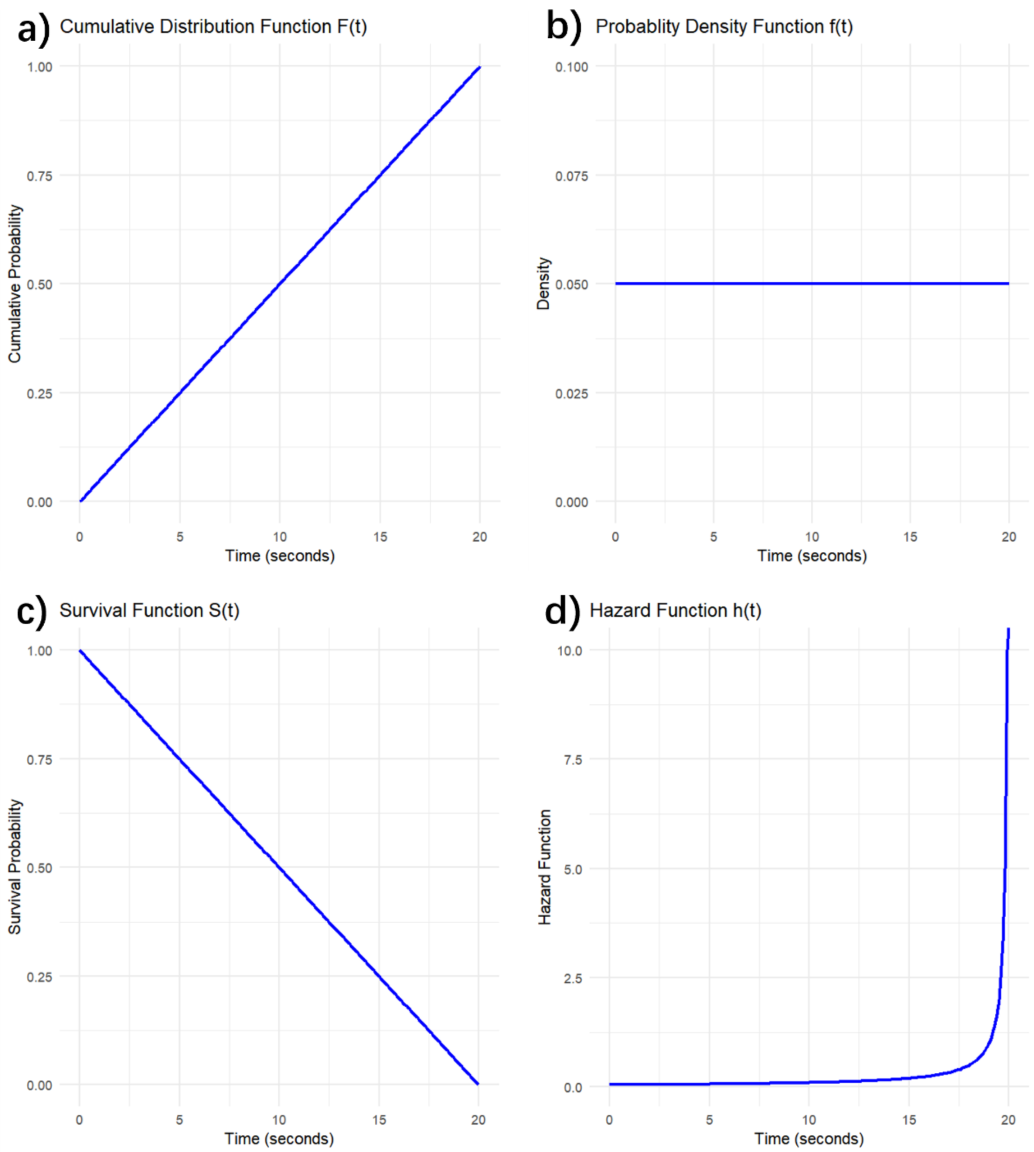

Figure 13: Four important concepts of survival analysis a) CDF, b) PDF, c) Survival function, d) Hazard function.

The introduction of the hazard function provides insights into the dynamics hazard associated with the event of interest, allowing researchers to understand how various covariates influence the hazard over time. Unlike traditional linear regression models that model time directly, a series of hazard-based regression models have been developed. These models are more flexible, and less affected by underlying assumptions. Most importantly, they offer significant advantages in handling censored data. They can also address late-entry variables and explore time-dependent coefficients in time-to-event data. Chapter 3.3.4 will focus on discussing regression models.

3.3.4 Regression model selection

Regression models in survival analysis are essential tools for understanding the relationship between covariates and the time until an event occurs. There are two main types of regression models. The first type is a family of hazard-based models, the most famous of which is the Cox proportional hazards model (Cox). The second type is models that directly focus on survival time, such as the accelerated failure time (AFT) model. Based on Cox and AFT, scholars have developed many new models to optimize the limitations present in the original models. In terms of model selection, I will discuss which regression model is better to use in this study, considering the challenges of regression analysis presented in 3.3.1.

In response to the underlying assumption, the original Cox model assumed that hazard is proportional (PH), which means that relative hazard remains constant over time for different levels of predictors covariates. This assumption brought significant limitations on the Cox model. This is because assuming the effect of a covariate on hazard is constant is not aligned with many situations (Lo et al., 2020). If the Cox model is still chosen for regression modeling without this assumption being met, it could lead to potentially biased results (Kim et al., 2015). However, some of the Cox-based models that have recently been newly developed can bypass that assumption by allowing the effect of covariates on Hazard to change (Liu et al., 2018).

The AFT models also have the **underlying assumption** that the effect of covariates on survival time is accelerated or decelerated by a constant factor. In other words, it assumes that the relationship between covariates and survival time is a multiplicative scale. More specifically, a change in a covariate may cause survival time to become some constant multiple of what it was before. In addition to this, using the AFT model needs to be explicit about the type of distribution, e.g., exponential, log-log, log-normal, or Weibull, which is still limited, although the Weibull distribution already offers a great deal of flexibility (Royston & Lambert, 2011). Recently, a general parametric AFT model has been proposed, which provides more flexibility by using restricted cubic splines to model the baseline (Crowther et al., 2023). In general, although both the traditional Cox and AFT models have some assumption limitations, the newly developed models have been able to avoid these assumption limitations very well.

In terms of dealing with **censored data**, the biggest advantage of survival analysis is that it can deal with censored data more efficiently. The Cox model has the ability to deal with censored data since it was first proposed (Cox, 1972). The Cox model applies partial likelihood, which allows us to define survival distributions based on other covariates using an unspecified baseline survival function (Moore, 2016b). In the subsequent development of the Cox model, the approach to handling censored data has been preserved and optimized (Crowther et al., 2023; Royston & Lambert, 2011). In contrast to the Cox model, the AFT model also has the ability to handle censored data. One of the most prominent methods is the Buckley-James method (Buckley & James, 1979; Lai & Ying, 1991), which is an iterative method based on the expectation-maximization algorithm. However, this method is not very stable, especially when the amount of data is small (Hsu et al., 2015). In the subsequent development of the AFT model, some new approaches had been proposed to address the instability of the aft model when dealing with censored data, such as the use of a multiple imputation approach to derive two hazard scores to select an imputing hazard set for each censored observation (Hsu et al., 2015). Overall, both the Cox model and AFT model are capable of handling censored data, but the Cox model is more stable in handling censored data, especially for smaller datasets.

The **late entry variable** is a significant challenge to regression analysis. If it is not handled well, the results of parameter estimation of the covariate can be dramatically biased. The classical Cox modeling framework provides a way to deal with late entry covariate. Firstly, the data set is preprocessed, and the data format is adjusted to the 'start-stop' format based on the late entry covariate, as described in (Moore, 2016c). Then the partial likelihood is adjusted to achieve the regression modelling of the late entry covariate (Therneau, 1997). The method has been developed in its entirety in the 'survival' package for the R language. Comparatively, the AFT model does not perform as well in dealing with late entry covariates, and one of the possible reasons for this is that the AFT model is a full-parameter model that uses maximum likelihood estimation for parameter estimation. However, new extensions based on AFT that can handle late entry covariates are still proposed, such as the flexible parametric accelerated failure time model proposed in 2023 (Crowther et al., 2023), which theoretically confirms the possibility of the AFT model to handle late entry covariates. The Cox model has been more well-established in dealing with **late-entry covariates**, and the AFT model has been extended to deal with late entry variables in recent years. Comparatively speaking, the Cox model is more advantageous in this problem.

When considering the **time-varying effect**, both the initial Cox model and the AFT model do not take the time-varying effect into account well. This is mainly due to their underlying assumptions. The Cox model assumes that hazard is proportional (PH), which means that relative hazard remains constant over time, i.e. the effect of covariates on hazard is constant. The AFT model assumes that the effect of covariates on survival time is accelerated or decelerated by a constant factor, which means that the effect of covariates on time is constant in multiplicity. Some new developments were designed to release these limitations. For the Cox model, firstly Schoenfeld residuals can be used to help us determine if the covariate under study is proportional. If that coefficient exhibits no-proportionality, a Prentice modification of the Wilcoxon test could be used to solve this problem. Alternatively, it could be solved by by defining a time-dependent covariate, $g(t) = z * log(t)$, (Moore, 2016c). There are also many extensions of AFT to solve this problem, such as the latest flexible parametric accelerated failure time model. It is inspired by the Royston–Parmar flexible parametric model that uses restricted cubic splines to model time-dependent coefficients. It is transformed into the AFT model, helping the AFT model relax the constant acceleration factor assumption (Crowther et al., 2023). It can be found that after continuous iterations and developments, both the Cox model and the AFT model have the ability to deal with the time-dependent coefficient.

The content of the **model output** has a very important impact on the interpretation of the effect of covariates on the dependent variable, as well as the model prediction. In the Cox model, the object of regression modeling is hazard, and the interpretation of the regression coefficients in the Cox regression model is a little different from that of the coefficients in the traditional linear regression, mainly because the Cox regression model focuses on the changes in the hazard rate (HR) rather than modeling time directly. The Cox regression model has the form:

$$h(t|X) = h_0 * exp(\beta_1 X_1 + \ \beta_2 X_2 \ \cdots + \beta_n X_n)$$

where $h(t|X)$ is the hazard function for a given covariate X_n , h_0 is the baseline hazard function, β_n is the coefficients.

HR can be denoted as:

$$HR = exp(\beta_i)$$

HR indicates how the hazard rate changes when the covariate X_i is increased by one unit. This is explained as follows:

- If HR > 1, it means that a one-unit increase in the covariate X_i will **increase** the risk of an event, and the hazard rate is multiplied by the HR.
- If HR < 1, it means that a one-unit increase in the covariate X_i will **decrease** the risk of an event, and the hazard rate is multiplied by the HR.
- If HR = 1, it indicates that the covariate has **no effect** on the risk of an event occurring.

In the AFT model, the regression coefficients explain the accelerating or decelerating effect of the covariates on event times. Specifically, the coefficients in the AFT model describe how the covariates affect the degree of speeding up or slowing down of the arrival time to the event. The AFT model has the form:

$$log(T) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \cdots + \beta_n X_n + \epsilon$$

where T is the survival time, X_n is the covariates, β_n is the coefficients, ∈ represents the error term.

Acceleration Factor (AF) can be denoted as:

$$AF = exp(\beta_i)$$

- If AF >1, it means that every increase of one unit in the covariate X leads to a **longer** survival time, decelerating the occurrence of events, and the survival time increases by AF times
- If AF <1, it means that every increase of one unit in the covariate X leads to a **shorter** survival time, accelerating the occurrence of events, and the survival time decreases by AF times
- If AF =1, it indicates that the covariate has no effect on the survival time.

Compared to the interpretation of the HR, the interpretation of the AF can be considered more intuitive and can directly adjust survival time, increasing or decreasing survival time (Swindell, 2009).

In conclusion, Cox and AFT models have performed well in relaxing the basic assumptions, handling the censored data, and considering the time-dependent coefficient after continuous improvement and development. Cox based models show some advantages in dealing with the late entry variable and are more stable in dealing with the censored data. The AFT model has a more intuitive interpretation of the coefficient because it directly models time. However, according to the principle of interconversion between the survival function and risk function explained in 3.3.3, even if Cox is modelled on hazard, it can be converted to time scale as well. Therefore, I plan to use the **generalised survival models** developed based on Cox for regression modelling in this thesis (Liu et al., 2018).

Generalised Survival Models (GMS) could be denoted as $g(S(t|z))$, for link function *g*, survival *S*, time *t*, and covariates *z* (Liu et al., 2018). They are modelled by a linear predictor in terms of covariate effects and smooth time effects. Proportional hazards and proportional odds models are the important components of GMSs. In other words, GMS are significant extensions of Royston–Parmar models (Royston & Lambert, 2011), which are derived from Cox models. They allow the use of natural spline functions to create a set of basic functions for fitting non-linear relationships. Natural spline constructs smooth nonlinear effects for covariates through a set of knots and associated degrees of freedom. It also allows the use of degrees of freedom to control the flexibility of the natural spline function ns in modelling the baseline logarithmic cumulative risk. Also addresses the issue of time-varying coefficients. These models have already been implemented the models in R, rstpm2 package.

The derivation of specific mathematical formulas will not be discussed here; for specific mathematical formulas see (Liu et al., 2018). The interpretation of coefficients will be discussed specifically, and other forms that can be derived based on the output of the model will be explained. About the interpretation of the coefficient, since GMS is still essentially an extension of the Cox model, the significance of the coefficient derived from the regression is relatively the same as the Cox model. When interpreting the coefficient, it is often interpreted in terms of the HR (see the explanation from 3.3.3).

But HR is still not that intuitive to understand, especially when survival analysis is deployed to non-medical fields. When getting a coefficient of HR greater than 1, it indicates that this factor will make the hazard of map reactivation happening higher, in other words, the mobile map will be reactivated faster. In addition to HR, I also want to know how much a covariate change will accelerate this event. Specifically, how much faster will the mobile map be reactivated than it did before this covariate change? At this point, the hazard function or HR would not be able to give us this answer directly. However, according to the principle of interchangeability between the hazard function and the survival function discussed in 3.3.3, the corresponding survival function can be derived before and after the covariate change. It can then reveal the difference between the two survival functions how much of a change in time will be brought about by a change in one of the covariates. Specifical results will be shown in 4.3 and 4.4.

4. Results

In this chapter, I will first present the results of the extraction of dependent and independent variables. I will then report the fitting of the survival analysis model and provide the summary of the model in section 4.2. Section 4.3 will focus on the results related to RQ1 and HP1, and section 4.4 will primarily discuss the results for RQ2 and HP2.

4.1 Variable extraction

This section aims to give an overview of the results of variable extraction. Section 4.1.1 will mainly focus on the dependent variable extraction. Section 4.1.2 and section 4.1.3 will primarily focus on the independent variable extraction results of human and environmental factors. The results for variable extraction are the basis of survival model building. Understanding the distribution of dependent variables and corresponding independent variables will provide a deep insight into the regression model.

4.1.1 Descriptive analysis of dependent variable

As discussed in Section 3.2.2, in this study, the dependent variable is not the navigator, but rather the time to map reactivation corresponding to each map inactive phase. Across 863 pedestrian navigation trajectories, there were **3117 MIPs** in total, with **2494 map reactivation events** and **623 censored events**. For more details on censored data, please refer to the discussion in section 3.2.2. In survival analysis, when dealing with censored data, the time from the start of observation to the end is still counted as the time to the event of interest. There will be a specific column indicating whether the event of interest occurred or was censored.

In this dataset, the median TMR was 3.27 seconds, meaning that 50% of the mobile map reactivation occurred within 3.27 seconds after the map was locked during navigation. **Error! Reference source not found.** displays the distribution of TMR for 3117 MIPs. The data shows a pronounced right-skewed distribution, indicating that most map reactivation events occurred within a short time after the map was locked.

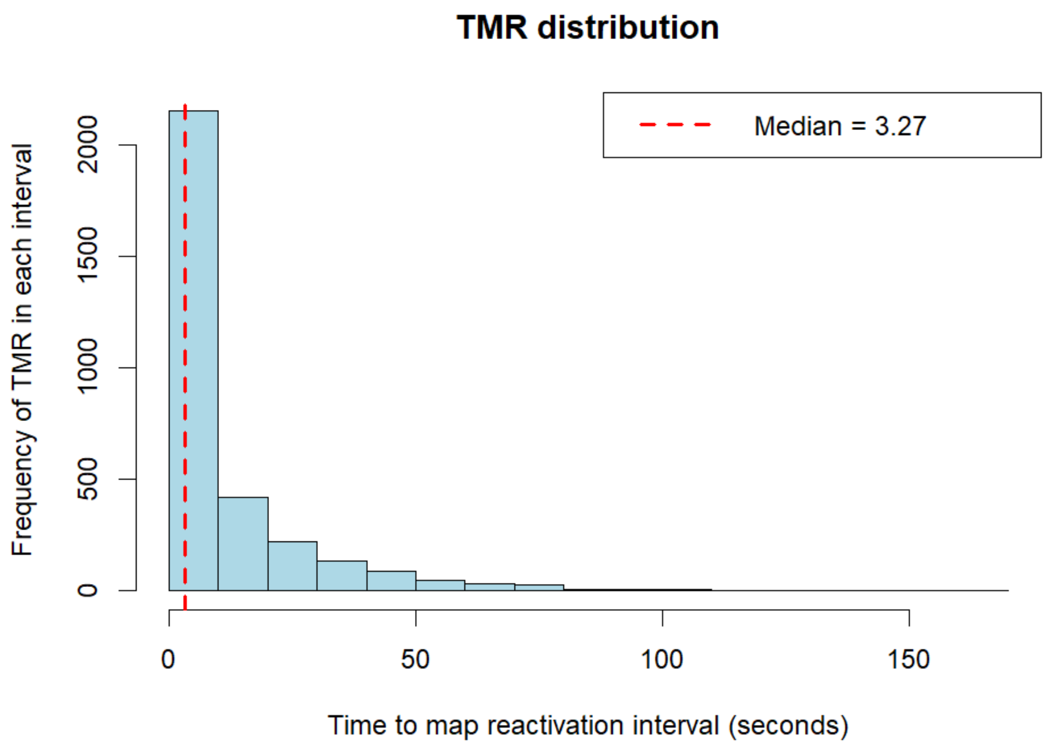

Figure 14 : The distribution of TMR for 3117 map inactive phase.

4.1.2 Descriptive analysis of human factors

It is important to emphasize again that since the subjects in this case are the MIPs, the extraction of independent variables is based on the 3,117 MIPs, rather than the participants. Human factors are participant-based variables, I need to map these human factors to each specific MIP. This involves assigning the age, gender, map use frequency, and SBSOD score of the participant corresponding to each MIP.

For the **age** factor, among the 54 participants, 23 were aged 18–24 years, 29 were between 25–34 years, and 2 were aged 35–44 years. After mapping the age factor to the MIPs, out of a total of 3,117 MIPs, the age group of 18-24 years accounts for 1,341 MIPs, while the age group of 25-34 years accounts for 1,703 MIPs, and the 35-44 years age group has fewer samples, with only 73 MIPs from this group. Figure 13 illustrates the specific age group distribution among the 54 participants and the 3,117 MIPs.

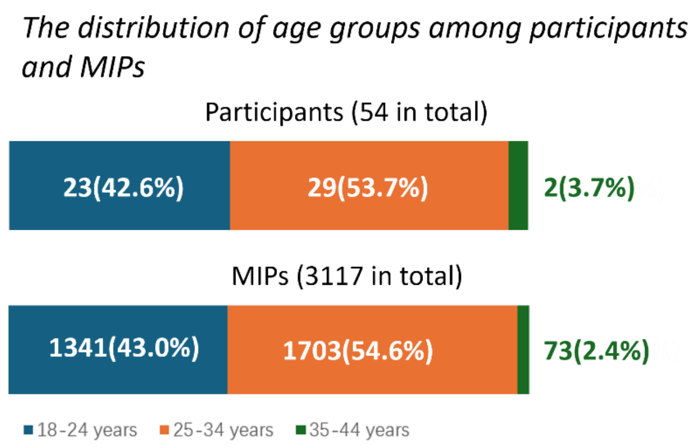

Figure 15: Distribution of the age factor among participants and MIPs, with their absolute values and percentages

In terms of the **gender** factor, there are 33 female and 21 male participants. After mapping gender to the MIPs, as Figure 14 shows, among all the MIPs, 2,112 are from female participants, while 1,005 MIPs are from male participants.

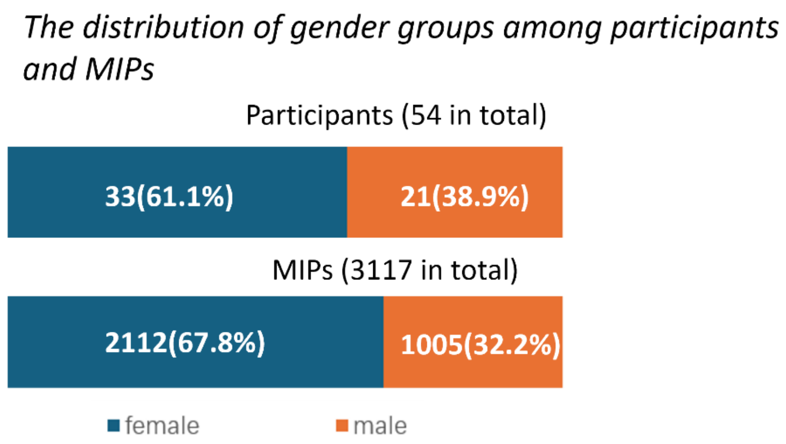

Figure 16: Distribution of the gender factor among participants and MIPs, with their absolute value and percentages

For **map use frequency**, it is categorized into three levels: "High" (four or more times a week), "Medium" (two to four times a week), and "Low" (a maximum of once per week). Among participants, they reported their weekly map use frequency, with 36 participants using the mobile map four or more times per week, 15 using it two to four times per week, and three participants using it no more than once per week. When mapping this variable to the MIPs, 2,273 MIPs correspond to high frequent map users, 709 to medium users, and only 135 MIPs come from low frequent map users (see Figure 17).

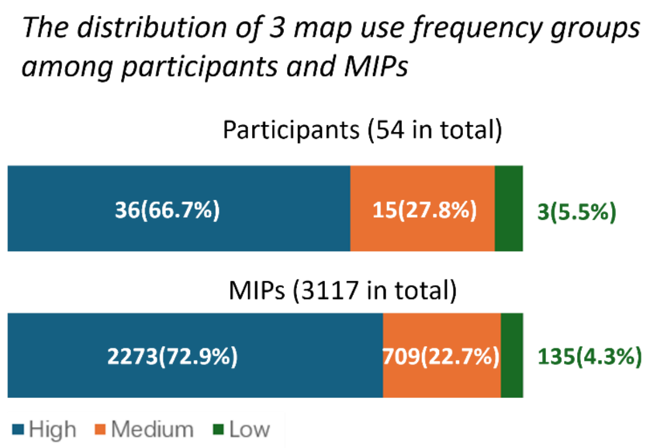

Figure 17: Distribution of the map use frequency independent variable among participants and MIPs, with their absolute value and percentages

Human factor **spatial ability** is reflected by the SBSOD score. The SBSOD scores are derived from each participant's performance on the SBSOD test, but they also need to be mapped to individual MIPs. Unlike categorical variables such as gender, age groups, and map use frequency groups, the SBSOD is a continuous variable. Here, I use a histogram to display the distribution of SBSOD scores among the MIPs. Figure 18 reveals that there are 1089 MIPs corresponding to participants with SBSOD scores between 4 and 5. Next, 874 MIPs are corresponding to participants with SBSOD scores between 5 and 6. For the other values and corresponding percentages please see Figure 18.

Figure 18: Distribution of the SBSOD independent variable among MIPs, with their absolute value and percentages

4.1.3 Descriptive analysis of environmental factors

Following the method for extracting environmental factors described in Section 3.2.3, I completed the extraction of these variables. Similarly, the environmental factors are also mapped to each map inactive phase under study. For **traffic density**, 1701 MIPs occurred under heavy traffic conditions, while 1416 MIPs occurred under light traffic conditions (see Figure 19).

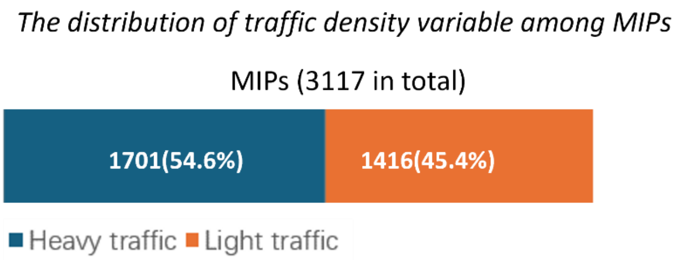

Figure 19: Distribution of the traffic density independent variable among MIPs with their absolute value and percentages

By the ratio by dividing the distance from the starting point of each MIP to the start of the route by the total length of the navigation route, I determined the route completion rate for each MIP. Based on the ratio, I identified whether the MIP occurred in the first half or the second half of the route. For the **route section** variable, 1843 MIPs occurred in the first half of the route, while 1274 MIPs occurred in the second half (see Figure 20).

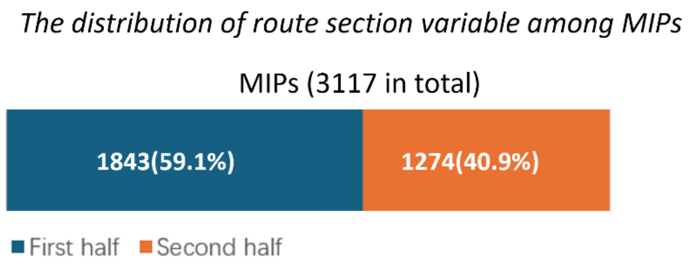

Figure 20: Distribution of the route section independent variable among MIPs with their absolute value and percentages

Whether MIPs belong to the pedestrian navigation trajectories that contain **shortcuts** can be determined by calculating the intersection between the trajectory and the building block of VE. After performing this calculation, 2,401 MIPs were found from trajectories without shortcuts, while 716 MIPs were from trajectories that involved shortcuts (see Figure 21).

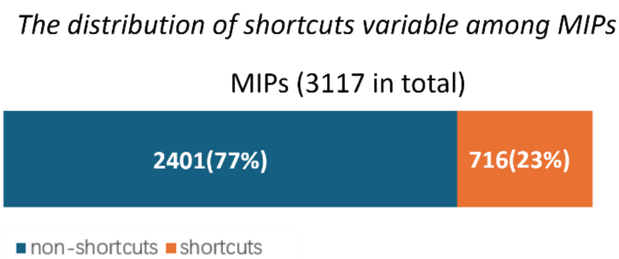

Figure 21: Distribution of the shortcuts independent variable among MIPs with their absolute value and percentages

By spatially intersecting the MIP trajectories with the road network in the VE, it allowed me to determine whether **road crossing** occurred during each MIP. After the calculations, it was found that 460 MIPs involved road crossings, while 2,657 MIPs did not involve any road crossings (see Figure 22).

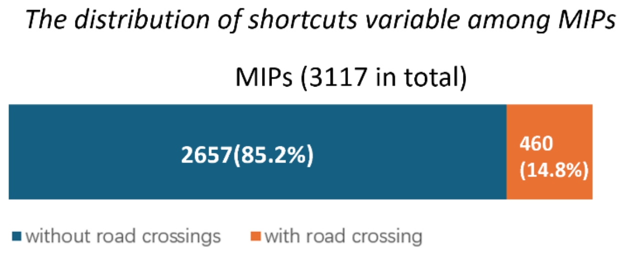

Figure 22: Distribution of the road crossing independent variable among MIPs with their absolute value and percentages

For the route length corresponding to MIPs, it is a continuous variable. In this dataset, there are 863 different navigation routes, which means there are 863 unique route lengths. When these route lengths are mapped to the corresponding MIPs, I obtained the distribution of route length among MIPs, as shown in Figure 23. It can be observed that 1,031 MIPs are from routes with lengths between 100-200 units, and 998 MIPs are from routes between 200-300 units. The values corresponding to other route length intervals are displayed in Figure 23.

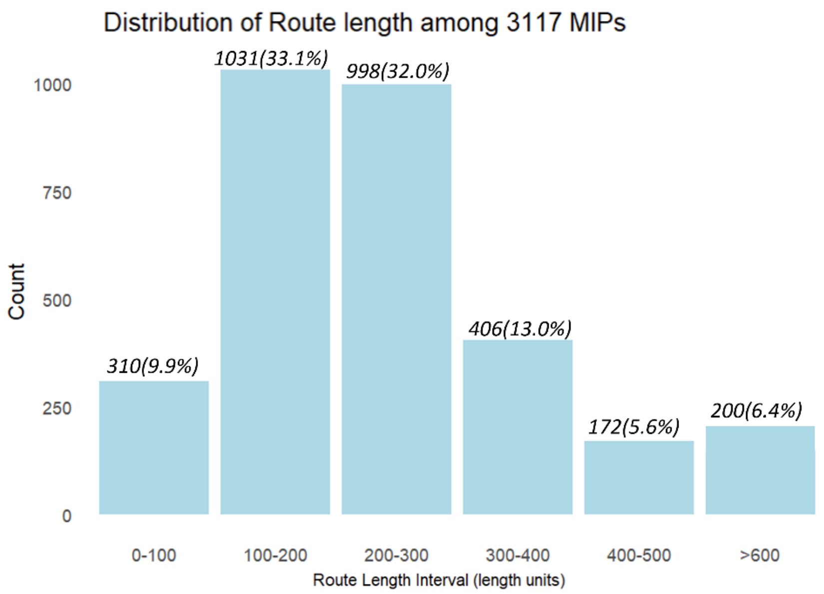

Figure 23: Distribution of the route length independent variable among MIPs, with their absolute value and percentages

4.2 Regression model

To show the result of the regression model, this section will follow a sequence: the result of correlation analysis among independent variables will be displayed first, followed by the result of feature selection and the result of model diagnostics.

4.2.1 Correlation analysis

Before conducting the regression analysis, I first performed a correlation analysis among the independent variables. This step is important as it helps identify the relationships between the independent variables. It can help to avoid the problem of multicollinearity, which can lead to biased estimates in the regression model and may affect the interpretability of the coefficients. Furthermore, correlation analysis can guide feature selection. For those independent variables that show a strong correlation with each other, it should be cautious to include them all in the regression model.

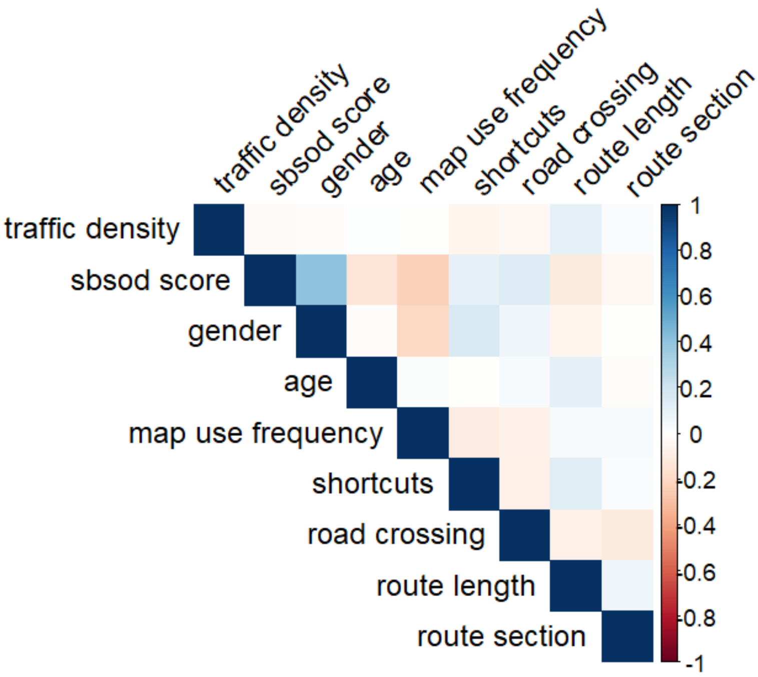

Figure 24: Correlation among Independent Variables

From the Figure 24, it can be observed that none of the independent variables exhibit strong correlations with one another. This indicates that multicollinearity is unlikely to be a major issue in the regression analysis, ensuring that the estimated coefficients for each variable will be reliable and interpretable.

4.2.2 Feature selection

To fit the GSM, a stepwise selection method was used to identify the most important factors from an initial set of four human factors and five environmental factors: age, gender, spatial ability, map use frequency, traffic density, route length, route section, shortcuts, and road crossing. Specifically, it begins by fitting a model that includes all the potential independent variables. Then, the significance of each variable was evaluated based on the p-value from statistical tests. At each step, the variable with the highest p-value that exceeds a pre-specified threshold, 0.05 in this case, was removed from the model. The stepwise approach allowed for a systematic assessment of the contribution of each variable to the model. The Table 1 presents the results when all independent variables are included in the regression model.

	β value	SE	Z	P
Intercept	-9.244	0.305	-30.302	<.001
age	-0.176	0.038	-4.669	<.001
gender	-0.053	0.050	-1.061	.288
SBSOD score	-0.228	0.019	-11.808	<.001
map use frequency	0.185	0.040	4.668	<.001
traffic density	-0.008	0.041	-0.206	.836
route section	-0.131	0.043	-3.052	.002
shortcuts	0.100	0.049	2.042	.041
route length	0.001	0.000	7.828	<.001
road crossing	-0.054	0.071	-0.755	.45

Table 1: Summary table of all independent variables effect on TMR

As a result of the variable selection process, six key predictors were selected as statistically significant: age, spatial ability (as measured by SBSOD score), map use frequency, route length, route section, and shortcuts. These variables demonstrated a significant impact on the TMR and were retained in the final regression model for further analysis. In contrast, variables such as gender, traffic density, and road crossing were found to be less significant and were subsequently excluded from the model to improve its accuracy and interpretability. This refined model focuses on the most influential factor, providing a clearer understanding of what factors will influence the time to map reactivation during map-assisted pedestrian navigation.

After identifying the independent variables that have a significant effect on the model, I further tested the degrees of freedom of the model. I fitted a series of GSMs with different degrees of freedom to determine the optimal model complexity. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to compare these models. The results (see Table 2) showed that the model had the lowest AIC and BIC values when the degree of freedom was set to 6, indicating that the model performed best in balancing goodness of fit and model complexity. Therefore, the model with a degree of freedom of 6 was finally selected for subsequent analyses.

Degree of freedom	AIC	BIC
1	15993.72	16043.25
2	15421.59	15477.32
3	14884.07	14945.99
4	14848.14	14916.25
5	14836.43	14910.73
6	**14802.6**	**14883.09**
7	14815.51	14902.19
8	14804.6	14897.48

Table 2: AIC and BIC comparison across different degrees of freedom for GSM

After determining the optimal degrees of freedom and identifying the statistically significant independent variables, I proceeded to refit the model. This resulted in the final model, as presented Table 3. The refined model includes only the variables that showed a significant effect on the outcome, ensuring a more accurate representation of the data. By excluding non-significant predictors, the model improves both interpretability and performance, allowing for more reliable predictions regarding the impact of the selected factors.

	β value	SE	Z	P
Intercept	-8.930	0.613	-14.546	<.001
age	-0.176	0.037	-4.719	<.001
SBSOD score	-0.233	0.018	-12.931	<.001
map use frequency	0.192	0.039	4.969	<.001
route section	-0.139	0.042	-3.267	.001
shortcuts	0.095	0.049	1.965	.049
route length	0.001	0.000	7.987	<.001

Table 3: Summary of the model with six degrees of freedom, including only significant influential factors

It is important to note that in survival analysis, the regression model coefficients (β) established for hazard are often interpreted in terms of the hazard ratio (HR) rather than the β values themselves. When the HR is greater than 1, it indicates that the covariate is associated with a higher hazard of the event of interest, which in this case is map reactivation. **An HR greater than 1 indicates a quicker map reactivation.** Conversely, **an HR less than 1 indicates a slower map reactivation**. The HR calculated based on the β values from the model are shown in the Table 4. The more detailed results directly related to RQ1 and RQ will be elaborated in sections 4.2 and 4.3.

	HR
Intercept	/
age	0.838
SBSOD score	0.792
map use frequency	1.211
route section	0.870
shortcuts	1.099
route length	1.001

Table 4: The HR corresponding to the independent variables, calculated as e^{β}.

4.2.3 Model diagnostics

When diagnosing survival analysis models, unlike linear regression models, it cannot directly compare predicted values with actual values. This is because the results derived from survival analysis are not specific values but instead survival curves under the conditions of given independent variables.

Therefore, to diagnose the regression models in survival analysis, it can compare the **predicted survival curves** fitted by the regression model with the **empirical survival curve** derived from the data itself. Based on this principle, this part conducted the comparisons by comparing the overall Kaplan-Meier (KM) curve from the data with the predicted curve generated by the model using the mean values of all independent variables as input to illustrate the model's fit. The KM curves reflect the survival probabilities in the observed data, for more discussion about the KM curve, please see section 3.3.3. The survival curve predicted by the model represented the survival probabilities predicted by the model based on the covariates. If these two curves are close to each other and follow the same trend in the graph, it indicates that the model fits the data well. At the same time, this graphical comparison can also help us to identify possible biases or anomalies in the model. Figure 25 showed that the model fitted well.

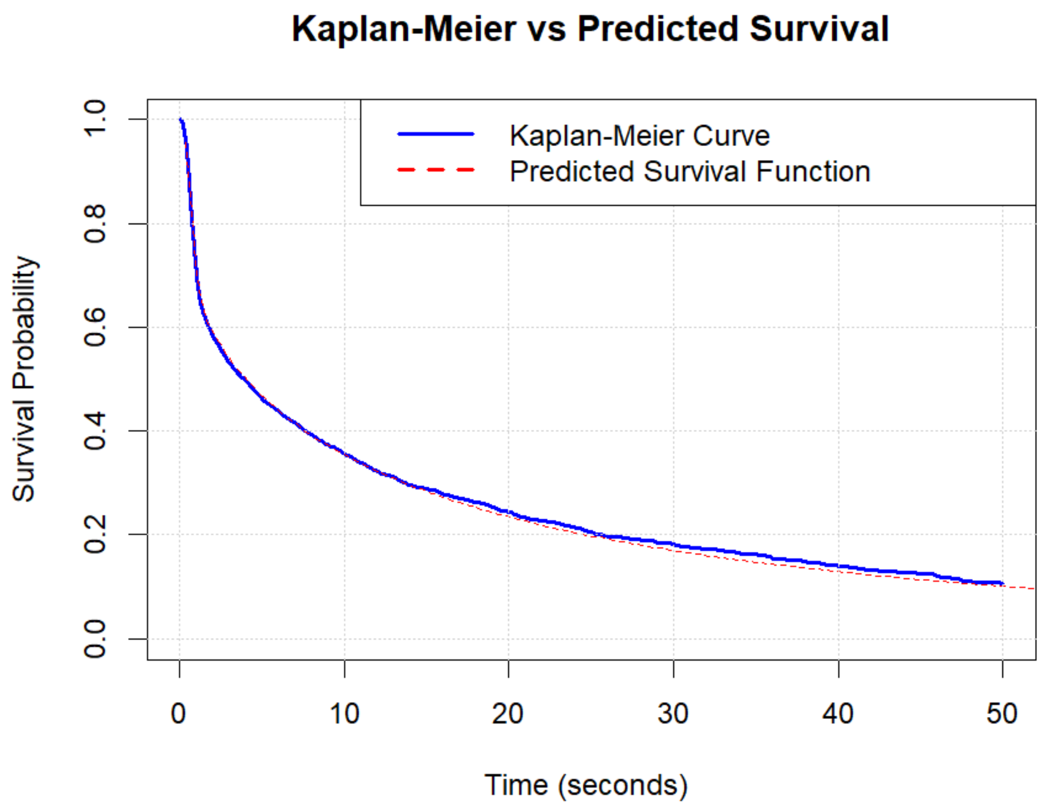

Figure 25 : KM curve from the observed samples vs predicted survival function with mean covariates

The Cox-Snell residual is another important diagnostic metric for a survival model (Ansin, 2015). It is used to measure the difference between observed and predicted survival times for each subject. If the model is well-fitted, the Cox-Snell residuals should follow an exponential distribution with a hazard ratio of one. After plotting the cumulative risk function $H(t)$ of the Cox-Snell residuals against the line $y = x$, a good model fit will have the cumulative hazard closely following the line $y = x$, which indicates that the residuals follow the expected exponential distribution. Figure 26 illustrates the goodness of fit of the model by comparing the cumulative risk function with the Cox-Snell residuals. Cox-Snell residuals also showed that the model had good fitness.

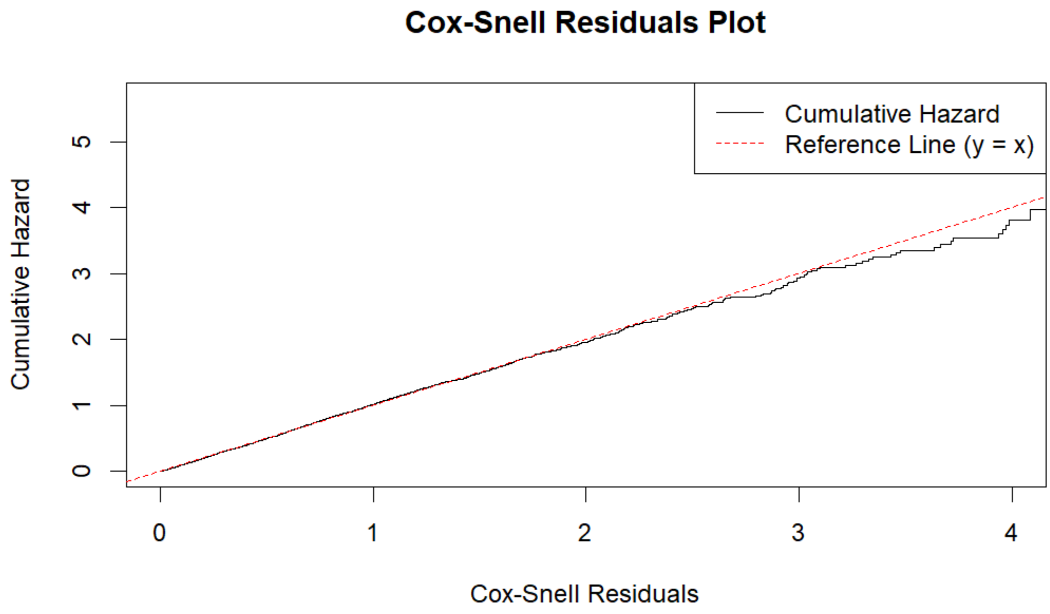

Figure 26 : Plots of Cox–Snell residuals from the GSM model

4.3 Results for human factors

In HP1, I hypothesized that older individuals would reactivate the map more slowly than younger individuals, males would reactivate the map more slowly than females, people with higher spatial abilities would reactivate the map more slowly, and those who use maps more frequently in their daily lives would reactivate the map more quickly.

In this chapter, I will verify the hypotheses made in HP1 based on the β values derived from the regression model and the **HR values** calculated from these β values. Here, I reiterate the interpretation of the hazard ratio (HR). When HR > 1, it indicates that an increase in the variable raises the hazard of map reactivation, resulting in a shorter TMR, meaning the map is reactivated more quickly. When HR = 1, the variable has no effect on TMR. Conversely, when HR < 1, an increase in the variable reduces the hazard of map reactivation, leading to a longer TMR, meaning the map is reactivated more slowly.

Nevertheless, HR only reflects the effect of the independent variables in terms of hazard—how the hazard of map reactivation changes when an independent variable changes. However, the concept of "hazard" cannot be directly applied to navigation assistance systems. One major advantage of survival analysis is that, based on the estimated hazard ratio, it allows me to obtain survival functions for specific values of predictors. Then point estimates could be derived for various quantiles of the distribution (e.g., the median). They are useful for predicting **when** the mobile map navigation system should provide guidance automatically.

Moreover, using the GSM in survival analysis also allows me to explore whether these variables have **time-varying effects**. In this case, it means examining whether the impact of changes in covariates on the hazard of map reactivation varies over time. For example, a variable may increase the hazard of map reactivation at 2 seconds of map inactivity, but after 10 seconds of inactivity, the same variable might have no impact on the probability of map reactivation. Investigating this is meaningful because it helps determine if the influence of certain variables on map reactivation strengthens or weakens as time progresses.

Therefore, in this chapter, when discussing the effects of human factors on TMR, I will first explore the impact of changes in independent variables on **HR**. Then, I will hold other variables constant while adjusting the variable under discussion to fit the survival curves, estimating the **median survival time** to interpret how changes in independent variables affect the dependent variable from a time perspective. Finally, I will investigate whether this covariate has a **time-varying effect**.

4.3.1 Age

From Table 4, it can be concluded that the HR corresponding to the covariate age is **0.84 ($p < 0.001$)**. This means that the hazard of map reactivation occurring becomes lower and the TMR becomes longer with increasing age. In other words, older individuals tend to reactivate the map more slowly.

By holding all other covariates at their mean values and setting the variable *age* to 0 (representing the 18-24 age group) and 1 (representing the 25-34 age group), I generated survival curves for these MIPs in these two age groups. From these survival curves, I calculated the median TMR for the two groups: 3.03 seconds for the 18-24 age group and 4.55 seconds for the 25-34 age group (see Figure 27). This indicates that as age increases from the 18-24 group to the 25-34 group, the median TMR extends by 1.52 seconds.

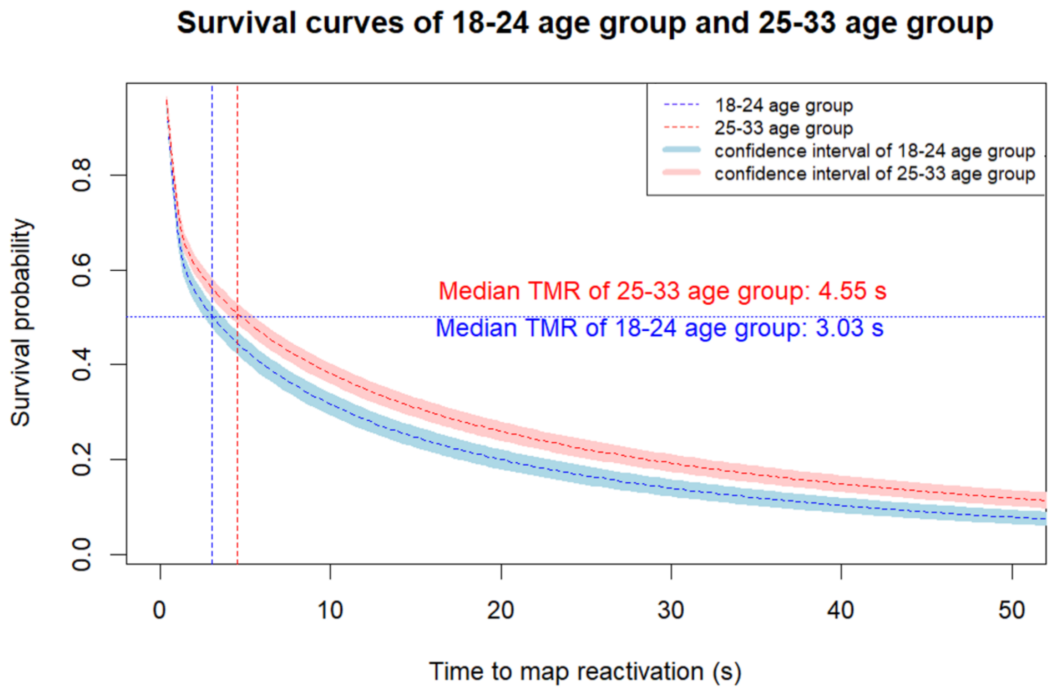

Figure 27: The survival curve for 18-24 age group (blue) vs. the survival curve for 25-33 age group (red). The 95 % confidence intervals are presented.

The GSM model can take account of time-varying effects of covariates. To explore whether a variable has time-varying effects, I compared the model with the age covariate considered as time-varying against the original model using ANOVA analysis. According to the result, the p-value was less than 0.001, which demonstrates that the age covariate has a time-varying effect.

From the Figure 28, it shows that the HR is predominantly less than 1, indicating that an increase in age reduces the hazard of map reactivation, leading to a longer TMR and a slower occurrence of map reactivation. The HR varies over time, suggesting that the impact of age on the hazard of map reactivation changes at different time points. At approximately 1.8 seconds, the HR reaches its minimum value of about 0.6, indicating that if the map remains inactive for 1.8 seconds, older individuals have only a 60% probability of reactivating the map compared to younger individuals at that time. After 6 seconds, the HR stabilizes around 0.83. This means if map inactivity remains beyond 6 seconds, although older individuals still have a lower probability of map reactivation compared to younger individuals, it rises to about 83%.

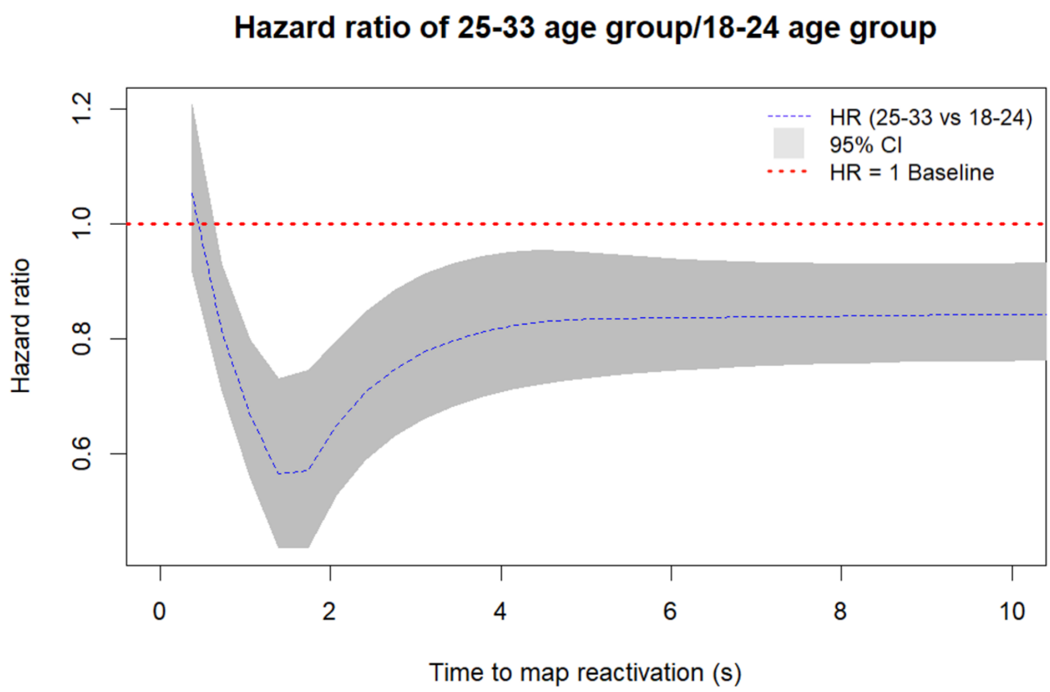

Figure 28: Time-Varying Hazard Ratio of the Age Covariate

Based on the HR values and the median estimates of TMR derived from the fitted survival curves, along with the time-varying effect of age on HR, I can conclude that contrary to HP1, an increase in age leads to an increase in TMR, indicating that map reactivation occurs more slowly.

4.3.2 Spatial ability

In terms of spatial ability, SBSOD score was used to reflect the spatial ability in this thesis. From Table 4, it can be found that the HR corresponding to the SBSOD score is **0.79 ($p < 0.001$)**. This means that the hazard of map reactivation occurring becomes lower and the TMR becomes longer with increasing spatial ability. In other words, people with higher spatial ability tend to reactivate the map more slowly.

By fixing the values of the other independent variables at their means and setting the SBSOD score to 5 and 6, I obtained the survival curves for two different SBSOD score groups. The median time to map reactivation for these groups was found to be 6.57 seconds and 10.1 seconds, respectively. This indicates that when the SBSOD score increases from 5 to 6, the median time to map reactivation increases by 3.53 seconds.

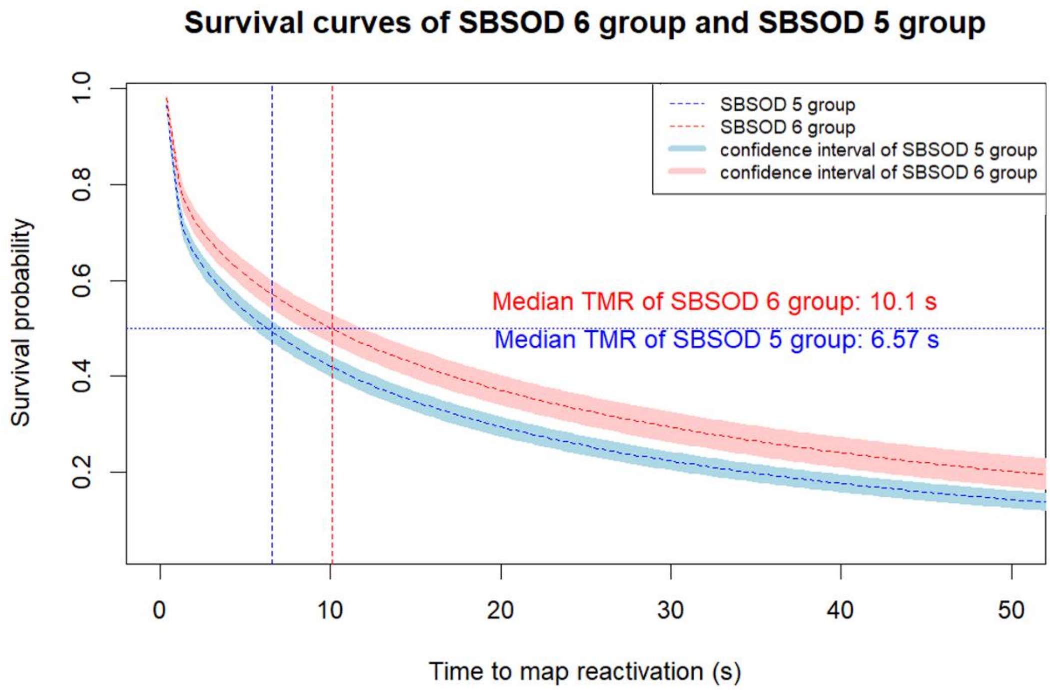

Figure 29: The survival curve for SBSOD 5 group (blue) vs. the survival curve SBSOD 6 group (red). The 95 % confidence intervals are presented.

To explore the time-varying effect of spatial ability, I incorporated the SBSOD score as a factor with the time-varying effect and conducted an ANOVA analysis with the previous model. The p-value from the ANOVA results of less than 0.001. This indicates that the SBSOD score also exhibits a time-varying effect. The Figure 30 illustrates how the HR associated with the SBSOD score changes over time. It can be observed that the HR consistently remains below 1, indicating that higher SBSOD scores reduce the hazard of map reactivation, resulting in longer TMR and slower map reactivation. The HR initially reaches its lowest value at approximately 0.7, suggesting that individuals with high spatial ability have the lowest probability of activating the map immediately after it becomes inactive, with a probability of only 70% compared to those with low spatial ability. However, if the map has remained inactive for more than 2 seconds, even though the probability of map reactivation for individuals with high spatial ability is still lower than that of those with low spatial ability, the probability of map reactivation increases to 80% compared to those with low spatial ability.

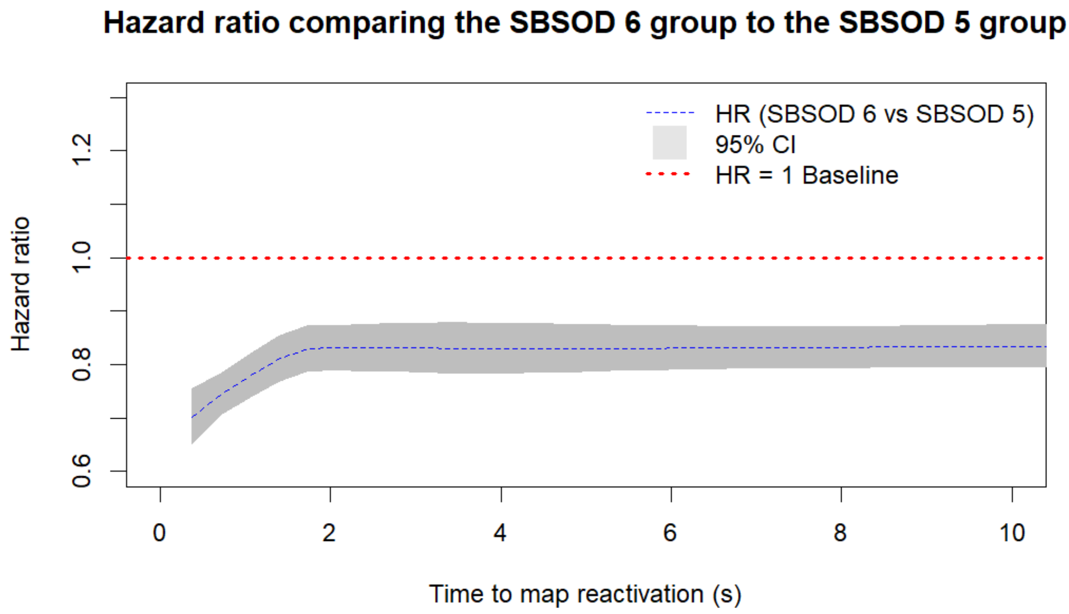

Figure 30: Time-Varying Hazard Ratio of the SBSOD score

Considering the HR values, the median estimates of TMR obtained from the fitted survival curves, and the time-varying effect of SBSOD score on HR, it can be concluded that, in line with HP1, a higher SBSOD score leads to a longer TMR. This indicates that people with higher spatial abilities tend to reactivate the map more slowly

4.3.3 Map use frequency

For the covariate **map use frequency**, there were three different frequencies of map use used by participants, namely 'High' (four or more times a week), 'Medium' (two to four times a week), and 'Low' (a maximum of once per week). Its corresponding HR of **1.21 ($p<0.001$)** could be extracted from Table 4, which means that the increase in map use frequency will raise the hazard of map reactivation and thus shorten the TMR. In other words, individuals who use the map more frequently tend to reactivate the map more quickly.

Similarly, by keeping the other independent variables at their mean values and adjusting the map use frequency to 2 (two to four times a week) and 3 (four or more times a week), I generated the survival curves for these two distinct map use frequency groups. The median time to map reactivation for these groups was calculated to be 5.56 seconds and 3.54 seconds, respectively. This suggests that as the map use frequency rises from medium to high, the median time to map reactivation is reduced by 2.02 seconds (see Figure 31).

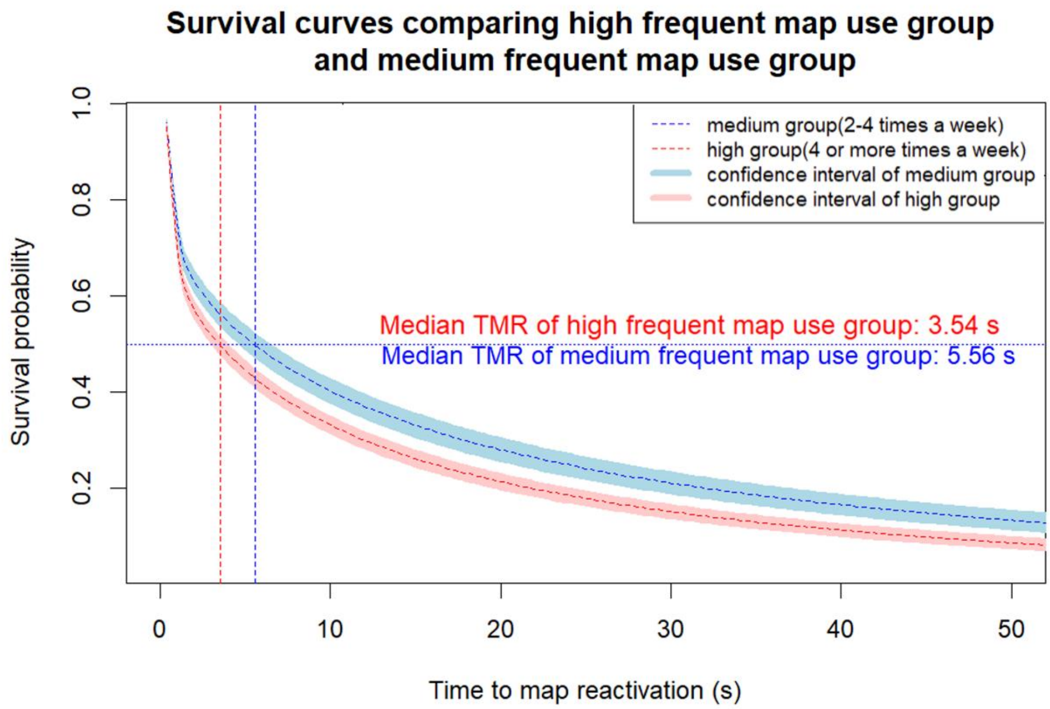

Figure 31: The survival curve for the medium frequent map use group (blue) vs. the survival curve for the high frequent map use group (red). The 95 % confidence intervals are presented.

Consistent with the previous methods, ANOVA analysis revealed a time-varying effect for the variable map use frequency (p = 0.046). Figure 32 illustrates that the HR is generally above 1. This indicates that individuals who use maps more frequently have a higher hazard of map reactivation, resulting in a shorter TMR and faster map reactivation. It can be observed that HR reaches its peak value of approximately 1.4 around the 2-second point. This suggests that if map inactivity lasts for 2 seconds, individuals who use maps frequently are 1.4 times more likely to activate the map compared to those who use maps moderately. As time goes on, although the hazard of map reactivation for frequent users remains higher than that for moderate users, the relative HR stabilizes around 1.2.

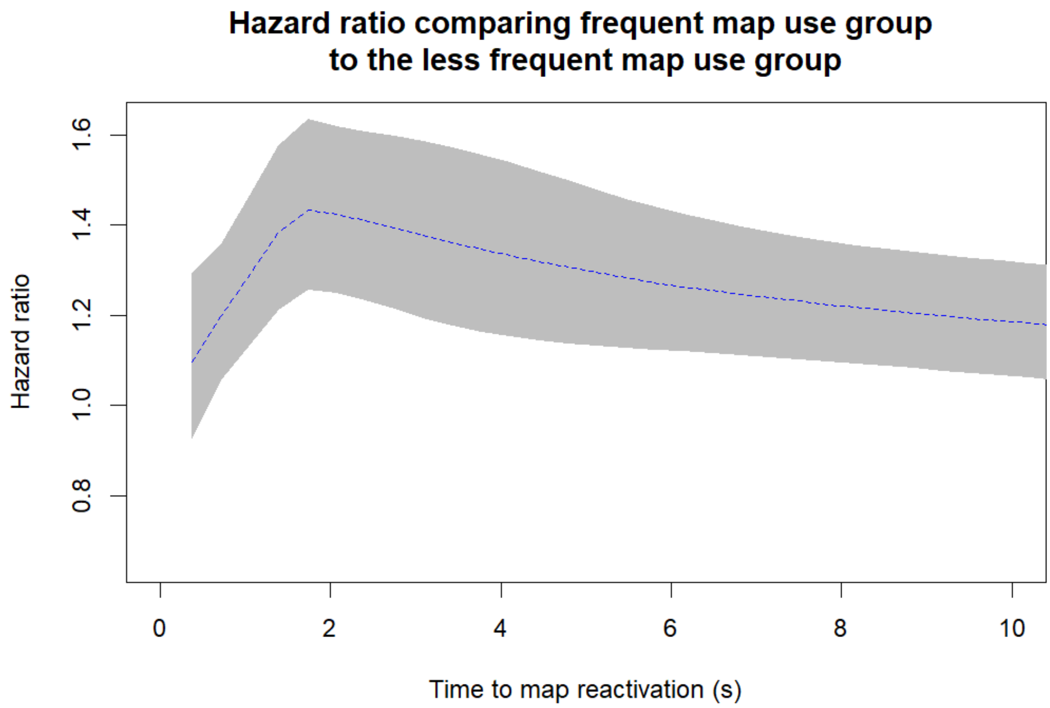

Figure 32: Time-Varying Hazard Ratio of the map use frequency

Taking into account the HR values, median TMR estimates from the fitted survival curves, and the time-varying effect of map use frequency on HR, it can be concluded that, consistent with HP1, individuals who use maps more frequently experience a shorter TMR. This suggests that frequent map users are likely to reactivate the map more quickly.

4.3.4 Gender

From Table 1, it can be observed that the coefficient for gender from the regression model is -0.053, with a p-value of 0.288. This indicates that gender does not have a significant effect on TMR. This is inconsistent with HP1 which females have a shorter TMR and reactivate the map more quickly.

4.4 Results for environmental factors

In HP2, it is hypothesized that heavy traffic and shortcuts will lead to quicker map reactivation. Additionally, map reactivation is expected to occur more quickly in the second half of the road, while longer road lengths will also contribute to faster map reactivation. Conversely, map reactivation from MIP which involves road crossings will happen more slowly.

Consistent with the methods used in section 4.3, this chapter will first examine the HR corresponding to these environmental factors. Next, I will keep other variables constant while varying the focus variable to fit the survival curves and estimate the median survival time, allowing for an interpretation of how changes in environmental variables impact the dependent variable from a temporal perspective. Finally, I will assess whether these environmental factors exhibit time-varying effects.

4.4.1 Traffic density

The results from the model fitting (Table 1) indicate that the coefficient for traffic density is -0.008, with a p-value of 0.836. This finding is inconsistent with HP2, as traffic density did not demonstrate a significant effect on TMR.

4.4.2 Route section

For the route section, according to what is stated in 3.2.3, I divided the MIPs under study into the first half and the second half of the route. According to the results of the Table 4, the HR corresponding to the route section is **0.87 (p = 0.001)**, which means that if the map reactivation occurs in the second half of a navigation route, it will reduce the hazard of map reactivation, and thus increase the TMR. This means that individuals tend to reactivate the map more slowly in the second half of the road.

By setting the other independent variables to their mean values and adjusting the map section to 0 (first half of the route) and 1 (second half of the route), I generated the survival curves for these two route section groups. The median time to map reactivation for these route section groups was found to be 3.03 seconds for the first half and 4.04 seconds for the second half. This indicates that the median TMR in the second half of the route is 1.01 seconds longer than in the first half (see Figure 33).

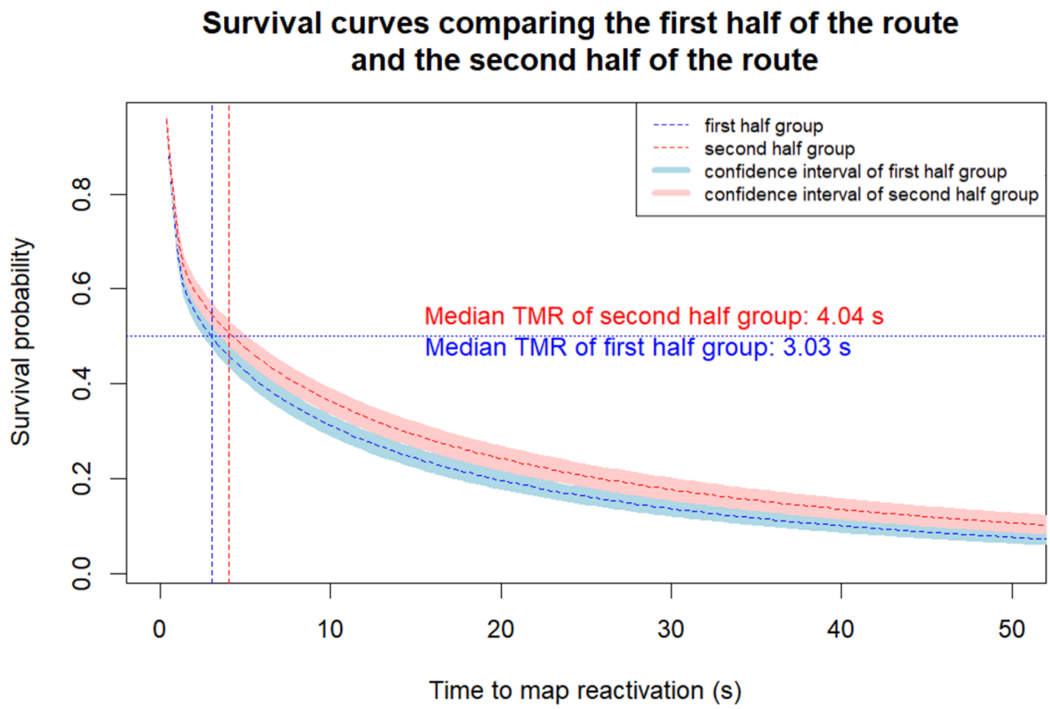

Figure 33: The survival curve for first half group (blue) vs. the survival curve for second half group (red). The 95 % confidence intervals are presented.

After incorporating the time-varying effect for the route section and conducting an ANOVA analysis, the p-value from ANOVA analysis was found to be 0.558. This indicates that there is no significant time-varying effect associated with the route section. Overall, based on the HR and the median TMR obtained from the fitted curves, it can be concluded that consistent with HP2, the TMR is longer in the second half of the navigation route. This indicates that individuals tend to reactivate the map more slowly during the second half of their navigation route.

4.4.3 Shortcuts

In the analysis of the independent variable shortcuts, the HR corresponds to this covariate is **1.1 (p = 0.049)** according to the Table 4. It means that the hazard of map inactivation occurring in shortcuts is elevated, which in turn leads to a shorter TMR. In other words, navigators tend to reactivate the map more quickly when taking shortcuts.

By fixing the other independent variables at their mean values and categorizing the shortcuts as 0 (non-shortcuts) and 1 (shortcuts), I created the survival curves for both groups (see Figure 34). The median TMR for the shortcuts group was 3.03 seconds, while for the non-shortcuts group, it was 3.54 seconds. This suggests that the median TMR is 0.51 seconds shorter when shortcuts are taken compared to routes without shortcuts.

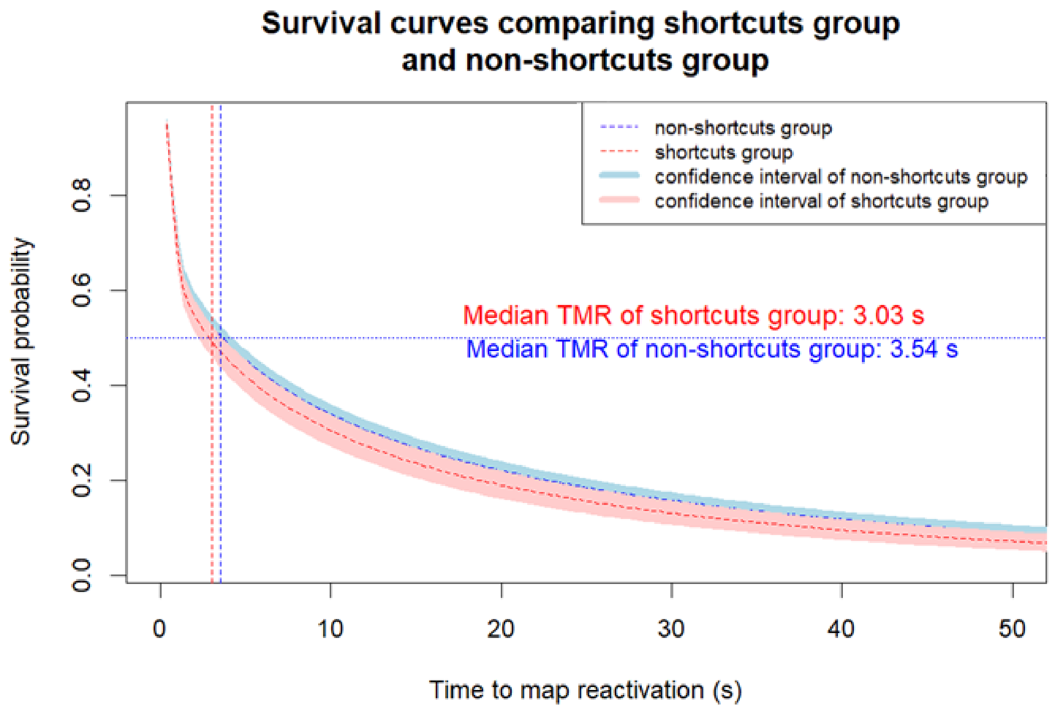

Figure 34: The survival curve for non-shortcuts group (blue) vs. the shortcuts group (red). The 95 % confidence intervals are presented.

After incorporating a time-varying effect for the independent variable shortcuts, the ANOVA analysis showed a p-value of 0.08. This indicates that the variable shortcuts did not show a significant time-varying effect. Based on the HR associated with the shortcuts variable and the median estimates of TMR derived from the fitted curves, it can be concluded that consistent with HP2, taking shortcuts results in a shorter TMR, indicating that people reactivate the map more quickly when utilizing shortcuts.

4.4.4 Route length

For the variable 'route length', it could be found that the corresponding HR is slightly greater than 1, with a p-value of 1.001, from Table 4. This reflects the fact that for every length unit increase in total route length, there is a slight increase in the hazard of map reactivation occurring in the navigation route, leading to a minor decrease in TMR. In other words, people tend to reactivate the map more quickly on longer navigation routes.

The Figure 35 shows the survival curves for TMR based on the fitted models for a 100-unit route and a 200-unit route. It can be observed that the median TMR for a length of 200 units is 1.01 seconds shorter than that for a length of 100 units.

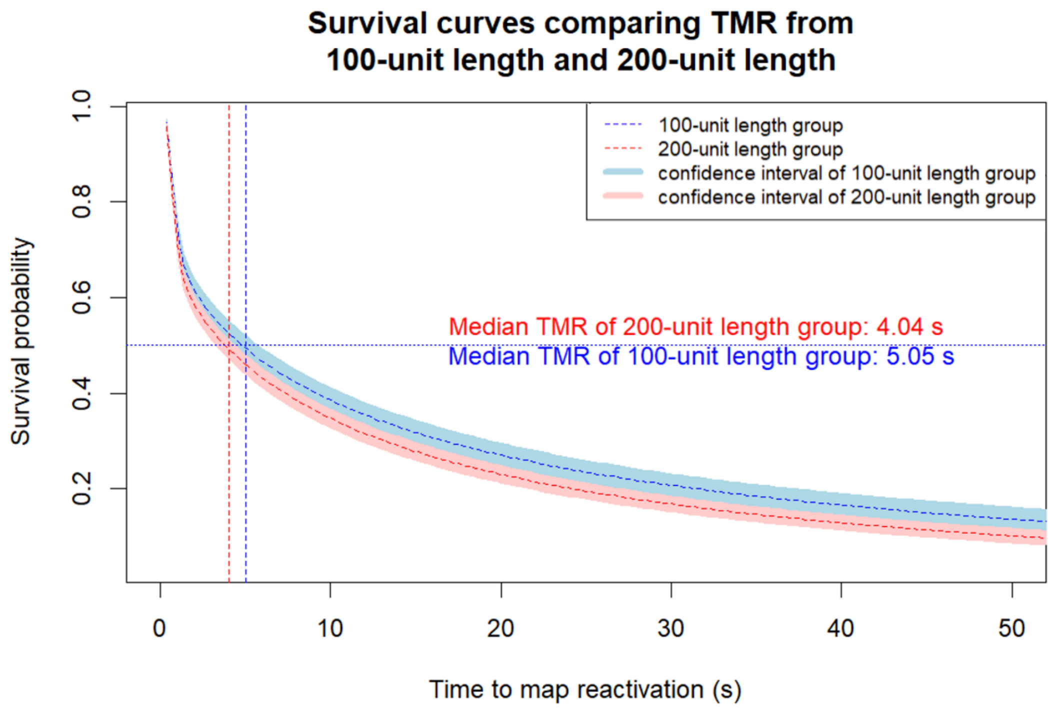

Figure 35: The survival curve for the long route length (200 units) group (blue) vs. the short length (100 units) group (red). The 95 % confidence intervals are presented.

After incorporating the time-varying effect for route length and conducting an ANOVA analysis, the resulting p-value was 0.017, indicating that route length does exhibit a significant time-varying effect. However, due to the small of the HR associated with route length, the specific time-varying effect was not observable (see Figure 36). Based on the HR associated with route length and the median TMR estimates for routes of 100 and 200 units, the conclusion can be drawn that, consistent with HP2, an increase in route length leads to a shorter TMR. In other words, people tend to reactivate the map more quickly when navigating longer routes.

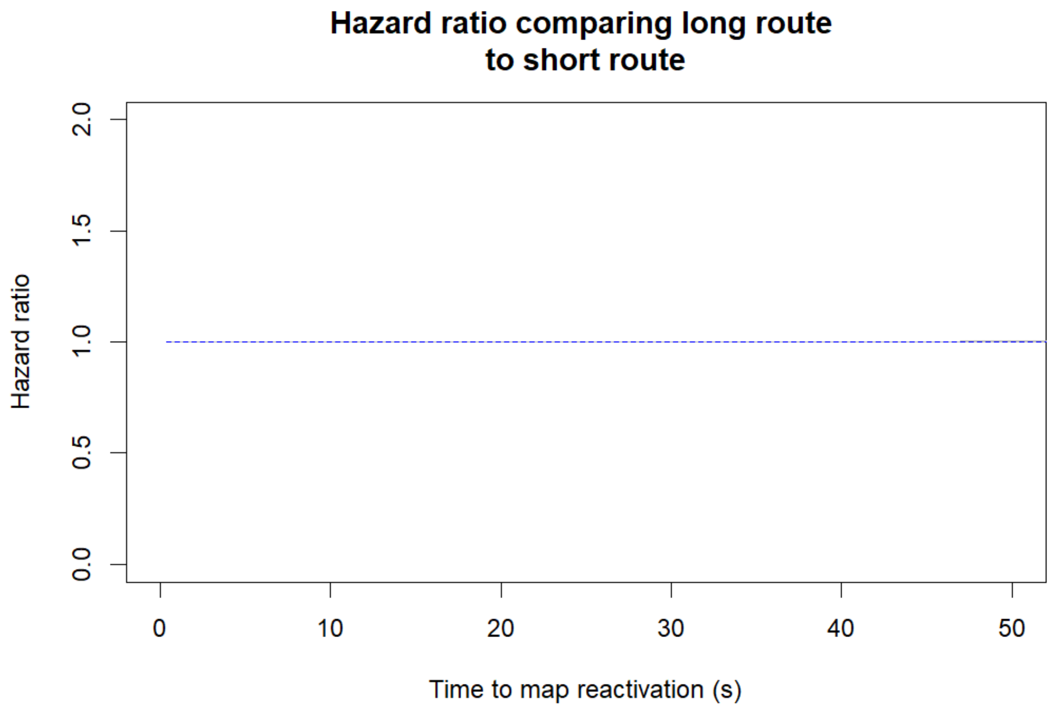

Figure 36: Time-Varying Hazard Ratio of route length

4.4.5 Road crossing

According to the results in Table 3, the β coefficient for the variable road crossing is -0.054, with a p-value of 0.45. This indicates that road crossing does not have a significant impact on TMR, which contradicts the hypothesis stated in HP2.

Overall, based on the results from the GSM model fit, the original hypothesis can be partially accepted. Three covariates—route section, whether shortcuts and total length of the navigation route—were found to significantly affect TMR. However, traffic density and road crossing did not show any significant effect. Among the three covariates with significant effects, the result of the total length of the navigation route aligns with the original hypothesis that an increase in the total length of the route will raise the hazard of map reactivation, which will lead to a shorter TMR. The presence of shortcuts also increases the risk of map reactivation risk and shortens the TMR. Moreover, the TMR for the second half of the route compared to the first half of the route, the hazard of map reactivation was reduced and the TMR became longer. This result is also consistent with that of the original hypothesis.

5. Discussion

This thesis contributed to the study area of when to provide navigation instructions. It significantly supplements existing research in this area (Giannopoulos et al., 2017; Golab et al., 2022). Specifically, it considered each moment the map becomes inactive as the starting point for determining when the next navigation instruction should be given. The guidance modality is in the form of a graphical navigation route on a mobile map. It explored how human factors—such as age, gender, spatial ability, and map use frequency—and environmental factors—such as route length, route section, shortcuts, road crossing, and traffic density—affect the time to map reactivation. Sections 5.1 and 5.2 will discuss the results of RQ1 and RQ2 respectively. Section 5.3 will discuss how the results could benefit the mobile navigation system. Section 5.4 will summarize the limitations of this study and point out future research directions.

5.1 Discussion of human factors

HP1 hypothesized human factors including age, map use frequency, spatial ability, and gender would influence the time to map reactivation. Specifically, older people, females, and pedestrians who use maps more frequently would reactivate the map more quickly. Pedestrians with a higher spatial ability would reactivate the map more slowly. This section will discuss the results compared to HP1.

5.1.1 Age

HP1 hypothesized that an increase in age would shorten TMR, meaning older pedestrians would reactivate the map more quickly during navigation. However, the results from the regression model showed the opposite conclusion: as age increases, TMR becomes longer, indicating that older navigators tend to reactivate the map more slowly during navigation.

One potential reason for getting contrary results could be the very close age range in this study. HP1 was formulated based on prior research about the age influence on navigation performance and map use. However, most of these studies have primarily focused on comparing younger adults with older adults, where younger adults are usually under 30 years old, and older adults are usually above 60 years old. A comprehensive review of age-related impacts on navigation also highlighted this point (van der Ham & Claessen, 2020). In this study, they described the age distribution among research about how age influences navigation in different age groups. It indicated the age distribution was notably skewed, with a focus on participants aged 18-30 and those over 60 years old (see Figure 37). This suggests that the effect of age on navigation performance may be more persuasive when comparing these more distinct age groups that have large age gaps. However, in this study, our two main age groups are 18-24 years and 25-33 years, which cannot directly reference the impact of age in comparisons between young and old adults, as was discussed in 2.2.1. This may lead to a bias in the hypothesis regarding the effect of age on TMR.

Alternatively, this study concludes that even closely related age groups, such as 18-24 years and 25-33 years, exhibit significant differences in navigation behavior and map use. This finding highlights the need for future research to go beyond the typical comparisons between younger and older adults. Researchers should consider closer age ranges when studying the impact of age on navigation and map use. Exploring a broader spectrum of age groups can provide deeper insights into how age influences navigation strategies and using behaviors on mobile maps across different stages of adulthood.

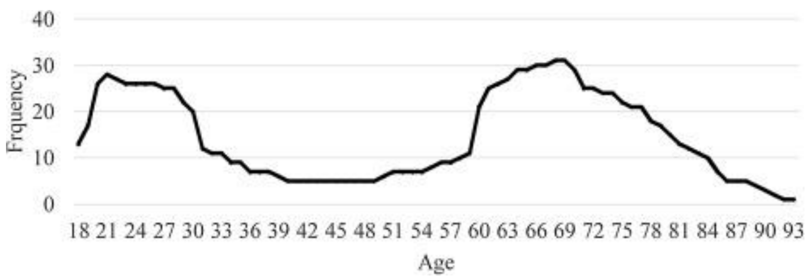

Figure 37: Age distribution of subjects in studies exploring the impact of age on navigation (van der Ham & Claessen, 2020).

5.1.2 Spatial ability

People with high spatial ability usually perform better in navigation, including enhanced spatial information acquisition, improved spatial memory, and overall better navigational skills (Kozhevnikov et al., 2006; Laczó et al., 2021; Ramanoël et al., 2020). For a more detailed exploration of these aspects, please refer to section 2.2.3. In this study, I similarly observed the influence of spatial ability on time to map reactivation, which is consistent with HP1. The results indicate that people with higher spatial ability tend to have longer TMRs, suggesting that they reactivate the map more slowly during navigation.

One potential explanation for this finding is that individuals with high spatial ability may rely more on their cognitive mapping skills and internal representations of the environment (Castellar & Juliasz, 2018). This helps them to pay more time and attention to the environment before rechecking the map. The slower map reactivation may also reflect a strategic approach to navigation, where they prefer to utilize their spatial skills instead of immediately relying on external aids such as mobile maps. This reliance on internal cognitive resources can potentially result in longer TMRs.

Furthermore, the analysis of the time-varying effect of spatial ability on TMR provides a deeper understanding of how spatial ability influences TMR. The results showed that, under the overall influence, spatial ability has the greatest impact at the moment immediately the map becomes inactive. Specifically, people with high spatial ability are significantly less likely to unlock the map right as it enters the inactive state compared to those with lower spatial ability.

5.1.3 Map use frequency

This study explored the impact of participants' self-reported weekly map use frequency on the time to map reactivation during map-assisted navigation. As discussed in section 2.2.4, the motivations for using maps in daily life extend beyond navigation needs, including various motivations such as checking points of POIs, viewing public transportation schedules, and other informational purposes (Brata & Liang, 2020; Farkas, 2016; Ying et al., 2020).

These diverse reasons for map use make it challenging to directly hypothesize how weekly mobile map use frequency impacts TMR. Nevertheless, I observed a significant effect of map use frequency on TMR. Consistent with HP1, participants who use maps more frequently have shorter TMRs. In other words, those who use mobile maps more frequently tend to reactivate the map more quickly during navigation. This finding suggests that self-reported weekly map use frequency is a reasonable indicator of participants' reliance on mobile maps for navigation, even though their overall usage includes non-navigation activities.

5.1.4 Gender

HP1 hypothesized that females might have a shorter TMR, meaning that females activate the map more quickly during navigation. However, based on the results from the regression model, gender did not appear to be a significant factor influencing TMR. This finding aligns with previous research outcomes which indicated no significant gender differences in navigation (Driscoll et al., 2005; Herman et al., 1979; O'Laughlin & Brubaker, 1998). This illustrates that gender may not play an important role in determining the time of map reactivation during navigation tasks.

5.2 Discussion for environmental factors

HP2 hypothesized environmental factors including traffic density, route section, route length, shortcuts, and road crossing would influence the time to map reactivation. Specifically, pedestrians navigating in heavy traffic density, in a longer route, and in shortcuts would reactivate the map more quickly. Pedestrians navigating in the second half of the route would reactivate the map more slowly. Similarly, if participants are crossing the road, they would reactivate the map more slowly. This section will discuss the results compared to the HP2.

5.2.1 Traffic density

In HP2, it was hypothesized that high traffic density would result in a shorter TMR, implying that people would reactivate the map more quickly when navigating in heavy-traffic environments. However, the results from the model fitting indicate that traffic density is not a significant factor influencing TMR. Contrary to the HP2, the heavy traffic did not have a significant impact on the time to map reactivation during navigation.

The main paper of this study also discussed that traffic density does not significantly affect map interaction or the completion time of navigation tasks (Bartling et al., 2024). This may be explained by the uneven distribution of traffic density within the virtual environment. Specifically, while navigating in the VE, certain areas may experience extremely high traffic density, causing participants to allocate additional attention to their surroundings to avoid collisions with other pedestrians. However, in other areas, even with increased traffic density, participants might still be able to move smoothly along the path. This uneven distribution could reduce the impact of traffic density on TMR, making it difficult to observe any significant effects.

Additionally, the heavy traffic density simulated in the VR environment still differs from real-world conditions. In the VE, even if participants collide with pedestrians or vehicles, they do not experience any real harm. As a result, some participants might ignore the need to be careful with others. However, in the real world, this is a serious issue as it directly impacts pedestrian safety during navigation (Zhang et al., 2022). Therefore, the effect of traffic density on TMR needs further investigation in real-world navigation tasks, where safety concerns play a critical role.

5.2.2 Route section

For the variable route section, HP2 hypothesized that TMR would be longer in the second half of the navigation route, meaning map reactivation would occur more slowly. The results align with this hypothesis. However, there was a potential risk that could have led to rejection when making this hypothesis. Specifically, as the navigator approaches the destination in the second half of the route, they might need to reactivate the map more quickly to check whether they are nearing their destination, driven by a destination recognition need for map use (Carpman & Grant, 2002).

From the results, this potential risk did not lead rejection of HP2. This suggests that the motivation to check the map for destination recognition only arises when the navigator is close enough to the destination. This also depends on the total length of the route. When the route is long, most map reactivations in the second half may not be directly related to destination recognition. However, when the route is short, the likelihood that map reactivation in the second half is linked to destination recognition becomes much higher.

5.2.3 Shortcuts

Consistent with HP2, the results revealed the significant impact of shortcuts on TMR, demonstrating that TMR is shorter on shortcut routes, meaning people reactivate the map more quickly. In section 2.3.2, I discussed the uncertainty in making assumptions about the shortcuts variable. On the one hand, people who tend to choose shortcuts often have higher spatial ability (Boone et al., 2019), which could lead to a longer TMR. On the other hand, shortcuts increase route uncertainty and reduce the navigator’s confidence in their memory of the route (Lancia et al., 2023), potentially resulting in a shorter TMR. Based on the results, it showed that the latter consideration that shortcuts reducing navigators’ confidence and leading to quicker map reactivation has a stronger impact.

Another point worth discussing is that the p-value for the shortcuts variable is 0.049, which is very close to the significance threshold of 0.05. One potential factor contributing to this borderline significance is the method used to extract the shortcuts variable. There will be a detailed discussion about this limitation in the section 5.4.

5.2.4 Route length

The analysis results support the HP2 that in longer navigation routes, TMR is shorter, meaning people navigating in longer routes would reactivate the mobile map more quickly. One reason might be that longer routes may increase the overall cognitive load for the navigator (Fu et al., 2015). As the route becomes more complex, there is a greater need for spatial updates and reassurance(Krichmar & He, 2023), which could need faster map reactivation. This aligns with research suggesting that people rely more on navigation aids when faced with longer, more demanding routes (Giannopoulos et al., 2017).

5.2.5 Road crossing

Inconsistent with HP1, I did not observe a significant effect of the road crossing variable on TMR. Road crossing is a typical late-entry variable (Matsuura & Eguchi, 2005). From the collected data, it can be found which MIPs involve road crossings and which do not. However, when the map enters the map inactive phase, it cannot be predicted whether or when a road crossing will occur. It is possible that a longer TMR leads to the occurrence of a road crossing, rather than the road crossing causing the TMR to increase. The study mentioned that using future events to predict outcomes is unscientific (Moore, 2016c), so such variables must be analyzed with great caution. This is also one of the strengths of survival analysis, which handles these variables effectively.

5.3 Implications for the navigation system

This thesis applies survival analysis to investigate the factors influencing TMR during navigation. The results indicate that age, spatial ability, map use frequency, route length, route section, and shortcuts all have a significant impact on TMR. These findings have practical applications for improving mobile map-based navigation systems, especially for optimizing the time of providing navigation instructions.

When applying theory to practice, it is crucial to consider whether the data required by the theoretical model is accessible at the practical level. In this case, all the variables found to significantly impact TMR are easily accessible at the application level. Specifically, user age and spatial ability can be obtained through user profiles and initial questionnaires like the SBSOD test (Hegarty et al., 2002). Map use frequency can be tracked directly by the mobile map application, providing more accurate data compared to the self-reported weekly map use frequency used in this study. Route length can be calculated by the navigation system once the user's destination is set, based on the route suggested by the algorithm (Du et al., 2019; Xu et al., 2016). Route sections and shortcuts can be dynamically detected using location-based services (Ariffin et al., 2011), which allows the system to determine at any given moment whether the pedestrian is on a shortcut or in which part of the route.

Based on these variables, the navigation system could generate survival curves for each map inactive phase. The navigation system could then use a quantile point estimate from survival curves, such as the median TMR, to determine when to proactively provide navigation instructions. The quantile point estimate could be selected according to the user's preferences. It is an improvement for pedestrian navigation, as mainstream mobile map applications like Google Maps only provide a single choice of 'more frequent and detailed audio announcements' (see Figure 38), rather than multiple choices for users.

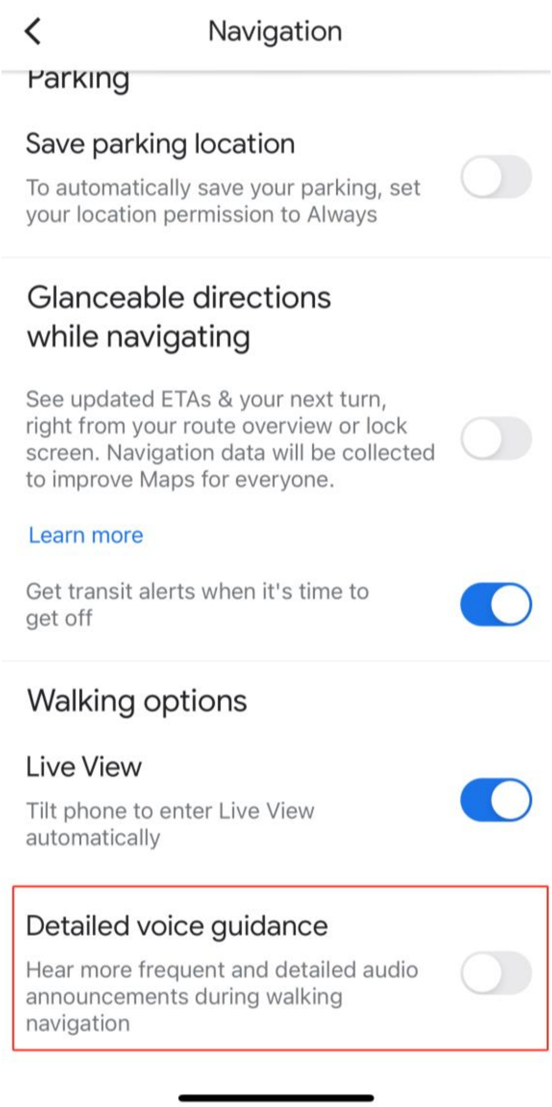

Figure 38: Google Maps walking navigation settings. (Google Maps, 2024)

This time predictions from Survival Analysis allow the navigation system to predict the probability of map reactivation at different time points based on user-specific information and location data. By implementing this method, the navigation system could automatically be aware of the probability that a user will reactivate the map at any given moment after it becomes inactive. This would allow the system to provide timely and proactive navigational instructions, helping to reduce cognitive load, enhance spatial learning, and offer a more seamless navigation experience for users. This proactive assistance could be beneficial in helping users stay oriented without frequent map-checking, thereby improving both the effectiveness and user experience of mobile navigation systems.

Two navigation scenarios are used to illustrate how navigation systems could utilize the results and model from this thesis to optimize the time of providing navigation instructions. **Scenario 1**: A pedestrian whose age is 27 years old. His SBSOD score was collected with the value of 4 when he first registered for this navigation system. His weekly map use frequency is 6 times a week from the application track data. Now he is navigating a route with a total length of 200 meters and in the first half of the route, following the recommended route from the system. A survival curve for Scenario 1 could be generated. **Scenario 2**: A pedestrian whose age is 18 years old. Her SBSOD score was collected with the value of 5 when she first registered for this navigation system. Her weekly map use frequency is 5 times a week from the application track data. Now she is navigating a route with a total length of 300 meters and in the first half of the route. She chooses to walk through a shortcut rather than follow the recommended route.

According to the survival curves (see Figure 39), the mobile map navigation system could provide navigation instructions proactively 2.6 seconds after the map is locked in scenario 1. In scenario 2, it could provide navigation instructions proactively 3.8 seconds after the map is locked. If the user prefers to get navigation instructions later, third-quarter TMR can be used rather than median TMR. This gives the flexibility of setting time for navigation instructions to the user.

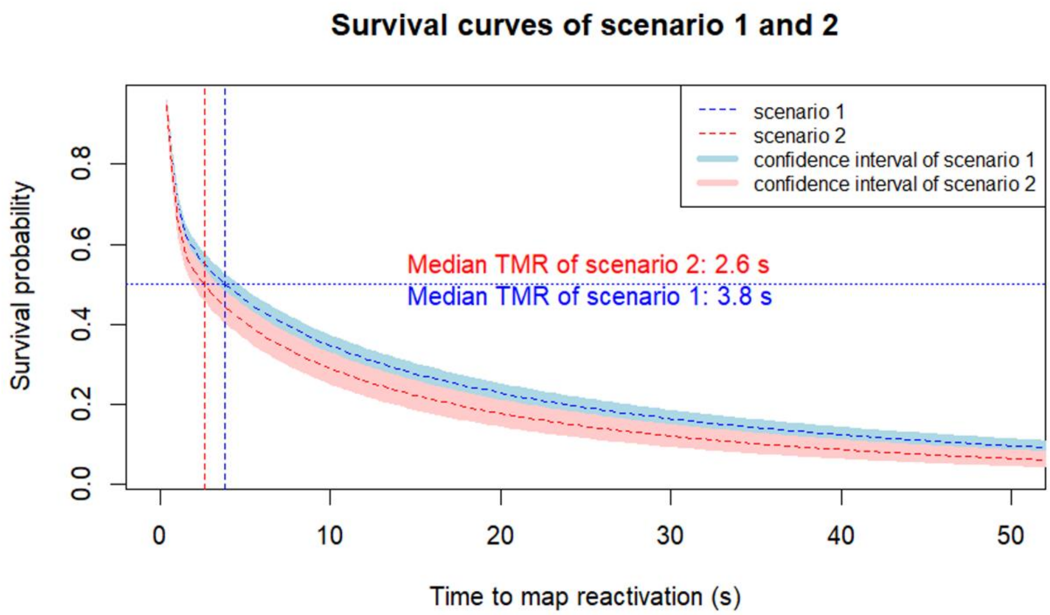

Figure 39: The survival curve for the scenario 1 (blue) vs. the scenario 2 (red). The 95 % confidence intervals are presented.

5.4 Limitations and future research

While this thesis found some significant results on the human and environmental factors influencing time to map reactivation during navigation, several limitations remain and are worth further investigation. One limitation is that the analysis in this thesis is based on pedestrian trajectory data collected in a virtual environment. However, pedestrian navigation and map use behaviors in the real world are different from those in a VR environment. In real-world navigation, interactions with mobile map systems involve dynamic elements such as avoiding obstacles and adapting to constantly changing surroundings (Zhang et al., 2022). The advantage of using a VR environment is that it provides a controlled setting where users can interact with digital maps in a more immersive environment (Cogné et al., 2017). VR allows researchers to control variables that are difficult to manage in real-world scenarios. However, despite these advantages, VR cannot fully simulate the complexities of real-world environments. Therefore, future research should aim to extend these findings to real-world navigation studies. Expanding this research direction into real-world settings would provide a more comprehensive understanding of when pedestrians need navigation guidance from navigation systems.

Another limitation of this thesis is the focus on analyzing when map reactivation occurs—that is when the map transitions from an inactive state to an active state. This is used to explore when users need spatial information provided by the navigation system. However, during the active map state, pedestrians also engage in shifts between the map view and the real-world navigation view. They may glance at the route on the map briefly before redirecting their attention to the real environment. Since I can only capture the active and inactive states of the map, it is difficult to determine whether pedestrians distribute their attention on the map during the map's active periods. Eye-tracking technology could offer a better solution to this issue. Eye tracking has been widely applied in the field of spatial cognition and has provided many new perspectives (Cheng et al., 2023; Giannopoulos et al., 2015; Kapaj et al., n.d.). Future research could integrate eye-tracking technology to capture how pedestrians allocate their visual attention to the map during navigation. This would allow for a more detailed understanding of how users balance their focus between digital maps and their surroundings during real-time navigation.

Additionally, since this thesis is based on an existing dataset, the variables that could be extracted for analysis were limited. There are several potential variables, particularly environmental factors such as the visibility of intersections (Giannopoulos et al., 2017) or the user's positional relationship to points of interest (POIs), that were not considered but are worth investigating. Future research could expand the range of variables to provide more comprehensive and in-depth perspectives on this topic. This broader exploration could lead to a deeper understanding of how various environmental and contextual factors influence the time of map reactivation during navigation.

Lastly, there is a limitation in processing the environmental factor shortcuts. In the current method, I assigned the label 'is shortcuts' to all MIPs along the entire route if a shortcut appeared at any point during navigation. The reason for this approach is that shortcuts could have a multifaceted influence on the navigator (Lancia et al., 2023), even on MIPs occurring before or after the actual shortcut. For example, pedestrians might need to check the map more frequently before getting into the shortcuts to make this decision. However, this method has limitations. If the shortcut comprises only a small portion of the overall route, the influence of the shortcuts on MIPs far from the shortcuts might be very small. Due to the scope of this thesis, I did not explore exactly how far-reaching the influence of shortcuts extends on map reactivation across the entire route. Investigating the precise extent of shortcut influence on MIP activation could be a potential direction for future research, helping to get a deeper understanding of how shortcuts affect navigational behavior.

6. Conclusion and outlook

In the research area about the time of navigation instructions given by pedestrian navigation systems, this thesis is the first to use each moment when the map becomes inactive as the starting point to investigate and graphic route displayed on the mobile map as the modality of navigation guidance. It aimed to explore which and how human factors (including age, gender, spatial ability, and map use frequency) and environmental factors (including route length, route section, shortcuts, traffic density, and road crossings) influence the time to map reactivation. The research is based on a large pedestrian trajectory dataset (Bartling et al., 2024), along with map interaction data collected from a mobile map navigation task conducted in a virtual environment. Survival Analysis methods were applied to statistically analyze the data.

My results showed that among the human factors, **age, spatial ability, and map use frequency** had significant effects on the time to map reactivation. Among the environmental factors, **route length**, **route section**, and **shortcuts** significantly affect the time to map reactivation. The following list of bullet points outlines how these factors specifically influence the time to map reactivation:

- Older pedestrians tend to reactivate the map more slowly
- Pedestrians with higher spatial ability reactivate the map more slowly
- Pedestrians who use map more frequently reactivate the map more quickly
- Pedestrians navigating longer routes reactivate the map more quickly
- Pedestrians navigating in the second half of the route reactivate the map more slowly
- Pedestrians navigating in route with shortcuts reactivate the map more quickly

The results of this thesis have significant practical implications for the design of pedestrian map navigation systems, especially for providing context-aware and appropriately timed navigation guidance. Specifically, the mobile map navigation system can obtain the influential factors dynamically according to the pedestrians' position and navigation context, such as in which route section or the length of the navigation route. Based on these factors, the navigation system can generate the survival curves of time to map reactivation in real-time. These survival curves indicate the probability of map reactivation across time. Then the navigation system can dynamically adjust the timing of navigation instructions based on user preferences, such as using the median survival time as a reference and integrating it with the survival curve.

This study supplements the existing research on context-aware map adaptations (Bartling et al., 2023) from the perspective of optimizing the timing of navigation instructions, while also contributing to the research framework of mobile map adaptation design (Fabrikant, 2023). Moreover, in the context of GeoAI (Janowicz et al., 2020), this study identifies key features that affect how long users will reactivate mobile maps again during navigation. This contributes to the feature engineering for the application of GeoAI in optimizing the time of providing navigation guidance, which can reduce cognitive load, ultimately improving the overall navigation experience.

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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. In addition, in this thesis, AI applications such as ChatGPT, and Grammarly were used to improve the writing and enhance the readability of the text.

Place, Date

Zurich, 01.10.2024

Signature

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