DIPLOMARBEIT

unter dem Titel

It's also about timing! When do pedestrians want to receive navigation instructions

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Abstract

In the design of pedestrian navigation systems, research has focused on *what* the route instruction should be, *how* to presented it but not *when* to present it to the user. This work aims to shed light on the potential of adapting timing to the wayfinder's preferences. Variables on personal, behavioral and environmental level were derived from data collected during an outdoor wayfinding study ($N = 52$). Participants followed navigation instructions to reach a destination and could request the instructions at any point in time and as often as they needed. Exploratory analysis was applied to determine driving variables in the observed behavioral processes by using survival analysis to predict when the user would like to listen to the instruction and generalized estimating equations to model population-average effects determining whether a user would like to hear a navigation instruction more than once. The results of this work suggest relevance of variables of all levels for the prediction of route instructions timing. Sense of direction, familiarity with the environment, personal characteristics such as *neuroticism* and *openness*, spatial strategies, age and landcover-related variables yield significance in our models and hint at the importance of personalization and adaption to variability of the environment in pedestrian navigation systems.

Preface

The starting point of my Diploma Thesis was the design of an experiment which aimed to collect data to address two main research questions, namely the question of whether it is possible to recognize a person's familiarity with the environment based on behavioral observations in a navigational setting and secondly, the prediction of preferred timing of route instructions. The acquisition of participants started in March 2020 and experiments were conducted between June and October 2020. After the experiments, I preprocessed the data and prepared it for further analysis. Prof. Ioannis Giannopoulos[3], Dr. Georgios Sarlas[4], Dr. Markus Kattenbeck[3] and I then worked on a paper about timing of navigation instruction and submitted it with the same title as this thesis to a special issue of *Spatial Cognition and Computation*. Our work encompassed the prediction of preferred timing of route instructions based on personal and environment data using survival analysis. I am lead author of the submitted paper and contributed by acquiring the data, preprocessing it, researching related work and writing the text together with Dr. Kattenbeck, Dr. Georgios Sarlas and Prof. Ioannis Giannopoulos. The present Diploma Thesis builds on the paper's content. I extended our work by adding a complementary analysis which focuses on identifying variables that influence someone to prefer to hear a route instruction more than once. The results of the analysis where similarly discussed as the ones of the submitted paper. At the time of submitting this thesis, the paper has not been published yet. Parts which were adopted from the original paper are flagged as such in the thesis, while the attachment focuses on my contributions to the work and details on participant acquisition, experiment procedure, data processing and contains the original paper in its state of submission.

The following footnotes will be used throughout the work and mark paragraphs that were directly adopted or adapted content from the original paper:

[1]Paragraph adopted from original article Golab, Kattenbeck, Sarlas, and Giannopoulos (n.d.)

[2]Paragraph adopted from Golab et al. (n.d.) and changed

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Acknowledgments

I would like to add a quote, here, by Dr. Markus Kattenbeck: "A master thesis is a collaboration between the supervisors and the student." This work definitely proved this and I want to express my gratitude for the continuous support and excellent supervision from Prof. Ioannis Giannopolous and Dr. Markus Kattenbeck, especially during these challenging times of conducting the experiment during the COVID-19 pandemic. Furthermore, I would like to thank Prof. Ioannis Giannopolous, Dr. Markus Kattenbeck and Dr. Georgios Sarlas for the exciting collaboration on the paper that underlies the present thesis. I further want to thank all the participants who have dedicated their time to take part in my experiment and friends and colleagues who have helped in the acquisition of further participants.

I would like to show my deepest appreciation to my father and grandparents who have generously supported me during my education and enabled me to keep my focus on my studies. Special thanks to Sergius for his encouragement and emotional support throughout the years and especially during the intense time of the experiment conduction. Lastly, I want to express great gratitude to my mother who has always made an effort to allow me to explore possible talents and follow my interests which led me to the studies of Geodesy and Geoinformation.

1. Introduction

Wayfinding has been a major topic of interest since the disciplines of geography and psychology have joined during the 1970s to research the acquisition of geographic knowledge, how it is structured within our minds and further, how it is used to find a way through the environment (R. M. Kitchin, Blades, & Golledge, 1997). Since then, researchers have been studying the concept of *cognitive maps* (R. M. Kitchin, 1994), developing methodology to measure a person's spatial abilities and strategies (e.g. Kozlowski & Bryant, 1977; Münzer & Hölscher, 2011) and exploring related decision making processes (Brunyé, Gardony, Holmes, & Taylor, 2018; Farr, Kleinschmidt, Yarlagadda, & Mengersen, 2012; Stern & Portugali, 1999a).

In the design of navigation aids, these concepts are used to understand a person's needs during wayfinding and to optimize navigation systems to facilitate the wayfinding activity as it is often referred to as a demanding task (e.g. Klippel, Richter, & Hansen, 2009; Stern & Portugali, 1999b). The cognitive load and complexity of the sequential decision making is attributed to user's characteristics, form of navigation aid and environmental factors (Giannopoulos, Kiefer, Raubal, Richter, & Thrash, 2014).

In the present thesis, we[5] retrieved variables on personal, environmental, and route level from data acquired during an outdoor experiment to assess their influence on the preferred timing of verbal route instructions. By doing this, we aimed to gain better understanding on the potential of reducing the cognitive load during wayfinding by adapting the timing of verbal route instructions to personal preferences and in dependence to environmental circumstances and route characteristics. This thesis was built on the work of Giannopoulos, Jonietz, Raubal, Sarlas, and Stähli (2017) which presents the first study focusing on the prediction of preferred timing of route instructions based on data acquired during a wayfinding study in a urban-like virtual environment. We applied a similar methodology in time-to-event modeling and further approach the topic of repeated navigation instructions by identifying possible reasons which cause a person to want to hear an instruction more than once.

In Section 2, approaches in the optimization of navigation systems in regards to concepts of spatial cognition are reviewed. In Section 3, readers are introduced to the setup and procedure of the study during which data was collected for the retrieval of variables and analysis which is explained in Section 4. We will discuss the resulting models and state interpretations about influential variables in Section 6, before a conclusion is drawn and an overview on identified research gaps is given (Section 7).

[5]Throughout the thesis, I will use the pronoun *we* for reasons of consistency as many parts of the work were adopted from Golab et al. (n.d.) in which pronoun *we* was used.

2. Related Work

[1]According to Montello (2005), navigation comprises two activities, wayfinding and locomotion. While locomotion describes the movement of one's body through the environment and includes tasks like avoiding obstacles, wayfinding encompasses route planning and all related decision-making processes to reach a given destination. During navigation, we constantly receive information about our physical environment through our senses and need to connect it with our knowledge to update our location and determine future decisions along our route. Theoretical reasoning and empirical evidence (see, e.g., Fang, Li, & Shaw, 2015; Giannopoulos et al., 2014; Schmidt, Beigl, & Gellersen, 1999), therefore, suggests that a wayfinder's cognitive load is impacted by personal characteristics, the environment and the actual route through this environment. Reducing the users' cognitive load is, hence, one of the major aims in designing wayfinding assistance systems. Scholars have pursued this objective by means of working (1) on the content, structure and presentation of route instructions and (2) adapting wayfinding systems to the user's personal needs. In this section, we will review both strands of prior work and, thereby, provide evidence for a lack of research on timing of route instructions, in particular for pedestrian navigation systems.

2.1. Research on route instructions

[1]While distance-based, on-line turn-by-turn instructions have been predominant in commercial applications, researchers have put emphasis on understanding the way humans communicate route instructions in order to mimick this way in wayfinding assistance systems for many years. Research on verbal human-to-human communication of route instructions and it's underlying cognitive processes (see, e.g., Hölscher, Tenbrink, & Wiener, 2011) revealed that landmarks are used frequently (see, e.g., Lovelace, Hegarty, & Montello, 1999; May, Ross, Bayer, & Tarkiainen, 2003; Michon & Denis, 2001) across different spatial environments (see, e.g., Sarjakoski et al., 2013, for hiking instructions). Empirical evidence has been provided that the use of landmarks has a positive impact on wayfinding performance (see, e.g., Ross, May, & Thompson, 2004; Tom & Denis, 2004) and that the absence of landmarks in an environment is compensated by an increased granularity of verbal human-to-human route instructions (see Hirtle, Richter, Srinivas, & Firth, 2010). Research on including landmarks (see Richter & Winter, 2014, for a thorough overview of the concept) in route instructions for wayfinding assistance systems has, consequently, become a predominant research topic, including modeling (see, e.g., Caduff & Timpf, 2008; Nothegger, Winter, & Raubal, 2004; Nuhn & Timpf, 2017; Raubal & Winter, 2002; Winter, 2003), empirical assessment (see, e.g., Götze & Boye, 2016; Kattenbeck, 2017; Kattenbeck, Nuhn, & Timpf, 2018; Quesnot & Roche, 2015) of salience and the automatic selection of landmarks (see, e.g., Duckham, Winter, & Robinson, 2010; Lander, Herbig, Löchtefeld, Wiehr, & Krüger, 2017; Lazem & Sheta, 2005; Rousell & Zipf, 2017; J. Wang & Ishikawa, 2018).

[1]Beyond the focus on important elements in human-to-human route instructions, researchers have worked on the formulation of route instructions in wayfinding assistance systems. The concept of *spatial chunking* (Klippel, Tappe, & Habel, 2002) has been of particular importance in these endeavours, as it reduces the cognitive load in wayfinders by reducing the level of granularity in route instructions. This idea was picked up

algorithmically (see, e.g., Richter & Klippel, 2005) and resulted in guidelines for cognitively ergonomic route directions (Klippel et al., 2009) which take, e.g., different levels of hierarchical spatial knowledge. In line with these guidelines empirical evidence also suggests that the granularity of route instructions increases in human-to-human route instructions if wayfinding decision situations lack landmarks (Hirtle et al., 2010). As the body of knowledge on adverse effects of wayfinding assistance systems on spatial knowledge acquisition grows (see, e.g., Ishikawa, 2019), scholars have also studied ways to overcome this issue. One very recent advancement in this domain are so-called orientation instructions (Schwering, Krukar, Li, Anacta, & Fuest, 2017) which enhance spatially chunked instructions by including additional environmental information to support acquisition of route and survey knowledge (see Krukar, Anacta, & Schwering, 2020, for empirical evidence that these instructions are superior to turn-by-turn or spatially chunked instructions without additional information).

[1]Neither the research efforts on landmarks nor on formulating route instructions reflect on how timing of a route instruction would have an impact on these. This lack of consideration holds also true for research on modalities and presentation of route instructions. Beyond the prevalent map-based approaches, reaserch on modalities and presentation modes has primarily focused on their impact on wayfinding effectiveness and efficiency by studying, for example augmented photographs (see, e.g., Walther-Franks & Malaka, 2008; J. Wang & Ishikawa, 2018), audio (e.g. Holland, Morse, & Gedenryd, 2002), augmented reality (see, e.g., Rehrl, Häusler, Leitinger, & Bell, 2014), vibro-tactile signals (see, e.g., Giannopoulos, Kiefer, & Raubal, 2015), and even music (see, e.g., Hazzard, Benford, & Burnett, 2014). Recently, however, studies on the presentation of instructions have also considered the reduction of attentional load (see, e.g., Stähli, Giannopoulos, & Raubal, 2020) and effect on spatial knowledge acquisition (see, e.g., Brügger, Richter, & Fabrikant, 2018).

2.2. Research on personalisation of wayfinding assistance systems

[1]Optimal wording, choosing the most suitable landmark among a set of candidates and the ideal presentation mode can, beyond general solutions, depend heavily on user characteristics. Personalization of wayfinding assistance systems has, consequently, seen increased interest. Researchers (see, e.g., Klippel et al., 2009; Zimmer, Münzer, & Baus, 2010) developed frameworks for the design of navigation aids emphasizing the adaption to user characteristics like spatial familiarity and spatial abilities. Empirical evidence has been collected for the increase in wayfinding performance through adaptation of, e.g., the presentation of route instructions to sense of direction (see, e.g., Bienk, Kattenbeck, Ludwig, Müller, & Ohm, 2013). Personal interests have also been incorporated into salience models, in order to be exploited for choosing personalized landmarks (see Nuhn & Timpf, 2020). Moreover, a large branch of research is dedicated to adapting systems to users with special needs, such as mobility impaired people (see, e.g., Barhorst-Cates, Rand, & Creem-Regehr, 2019; Cheraghi, Almadan, & Namboodiri, 2019) or visually compromised (see, e.g., Ding et al., 2007; Völkel & Weber, 2008) persons.

2.3. Timing

[1]So far, we have seen considerable effort dedicated to optimizing pedestrian wayfinding assistance systems with respect to the structure, granularity and presentation of route instructions, as well as adapting it to user's personal preferences and needs. All of these research efforts, however, neglect — with exception of Giannopoulos et al. (2017) — the key question of presenting a navigation instruction to a pedestrian at the right point in time. This is, on the one hand, in contrast to the attention timing has seen in research on car navigation systems (see below); on the other hand, it is also in contrast to empirical evidence (see, e.g., Brügger, Richter, & Fabrikant, 2019, who provide strong evidence for the way system behavior and wayfinder behavior interact) and theoretical claims. In their theoretical account based on Maslow's theory, Fang et al. (2015) emphasize the importance of the inclusion of personal preferences to be able to predict their behavior and to make pedestrians feel more comfortable by adjusting navigational instructions and interaction load with the navigation system as a response to the dynamic change of environment. This hints towards the importance of research on which factors influence the preferred timing of navigational instructions based on the user's personal preferences. Despite the fact that timing of route instructions is a desideratum with respect to pedestrian wayfinding, it has seen much interest in car navigation systems. This fact has been also stated by Giannopoulos et al. (2017), who present the first study on timing of pedestrian navigation instructions. As a starting point, the authors thoroughly reviewed literature on timing in car navigation systems and found several variables to be important: environmental factors (traffic, visibility of road signs), driver's characteristics (age, gender), driving speed and attributes of the navigational instruction (length, upcoming turn/maneuvre). Subsequently, the empirical part of their study, which was conducted in a virtual environment, found similar factors which influence user preferences in timing of pedestrian navigational instructions (see Giannopoulos et al., 2017, p. 16:9): These include personal characteristics like age and spatial abilities and route specific aspects such as the shape of the upcoming intersection, its visibility or the length of the route segment. Their findings are in line with empirical evidence that wayfinders make spatial decisions before the arrive at an intersection (see Brunyé et al., 2018) and accounts for the impact personal and spatial characteristics of the environment have on the complexity of wayfinding decision situations (Giannopoulos et al., 2014). Based on these considerations, the goal of the present study is to build on these results and study preferred timing of route instructions in-situ based on personal, environmental and route-related characteristics.

Moreover, within the experiments of Giannopoulos et al. (2017), participants were divided into two groups whereas participants in one group could request a navigation instruction only once and in the other, as often as the wanted. Only in 14.4% of the cases in the multiple-clicks condition, a route instruction was requested for a second time and they concluded that receiving it only once would be sufficient. In the underlying experiment to our work, all participants were allowed to request a navigation instruction multiple times and in about one third of all cases an instruction was requested for a second time or more. To work towards an understanding of why people would want to hear a navigation instruction more than once, we decided to further identify influential variables by means of solving a binary classification.

3. Experimental Design and Procedure

[1]In this section, the underlying experiment of this work is described in detail. It is important to note that the experiment was designed to collect data to address multiple research question, not only the ones discussed in the present work. We will only discuss the parts which are relevant to the present work.

Participation in the experiment involved two parts: the completion of an online questionnaire and the in-situ study. Routes for the in-situ study were chosen based on the information each participant provided in course of the questionnaire. We will, therefore, first describe the structure of the online questionnaire, how the obtained information from it was processed and then describe the procedure of the outdoor experiment.

3.1. Materials

3.1.1. Online questionnaire

The online questionnaire was designed to allow an anonymous registration for the experiment, collect personal variables by the means of questionnaires and spatial information to obtain routes for the outdoor experiment.

[1]The collected personal features of a participant encompassed demographic data, data on spatial strategies (FRS, Münzer & Hölscher, 2011) and personal characteristics based on the so-called Big Five Personality traits (Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2012). To collect routes, participants were asked to outline areas in Vienna they are familiar with using polygons as well as highlight and name places they know within these polygons. In order to ensure a reasonable experimental time, two of these places were randomly selected on the condition that they are 900m to 1.3km apart. One place of these served as a starting point, the other one was set as the destination and these roles were randomly assigned. Subsequently, we asked participants to sketch the route they would choose between these two points.

In this way, the participant's familiarity of the route was insured. This workflow is illustrated in Figure 1. Technical details on the online questionnaire and instructions for marking familiar places are described further in detail in Section A in the attachment.

3.1.2. Generating auditory route instructions

[2]In the preparation of the in-situ study, landmark-based instructions were designed. For this, the algorithm described by (Rousell & Zipf, 2017) was implemented in `Python 3.8` using building footprints retrieved from the *OSMNX*-library (Boeing, 2017) and Point of Interest (POI)-data downloaded from (*Geofabrik Download Server*, 2018). In short, this algorithm takes points of interest and buildings in a 50m-radius around a decision point into consideration of referencing it in the associated navigation instruction. Each object is assigned a suitability metric which is determined based on its uniqueness, advanced visibility, relative position to decision point and direction of travel and salience, and the object with highest suitability value is chosen. Before constructing the final navigation instructions, each route was visited to ensure that the landmarks selected by the algorithm were appropriate and would not induce ambiguity in the direction of the route instructions.

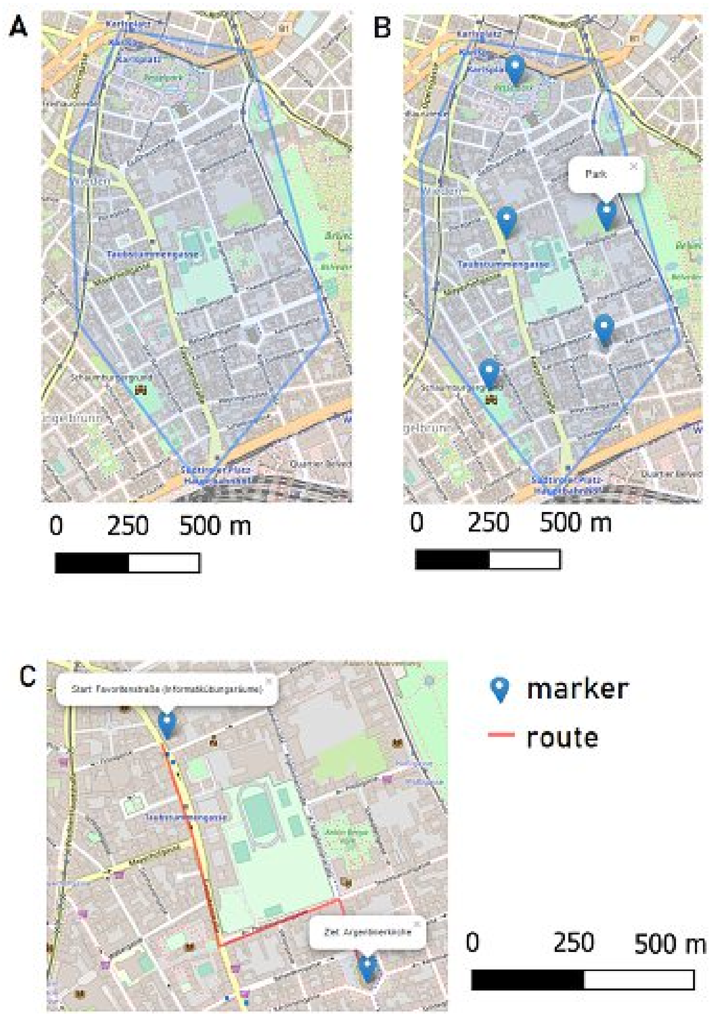

Figure 1: Illustration of process of obtaining routes. *Step 1*: Participant marks familiar area using a polygon (in blue), displayed in map **A**. *Step 2*: Markers are set on known places within these markers and add a description to each one(map **B**). 2 of these are randomly chosen on the conditions that they have to be within a certain distance (900m-1.3km) and are set within the same polygon.*Step 3*: Participant draws route she/he would choose between the randomly selected markers (map **C**). *backgrounds*: (OpenStreetMap contributors, 2017)

[1]Thereby, confounding effects stemming from inadequate object selection by the algorithm or incomplete OSM data was avoided. In a few cases, the algorithm was not able to determine a suitable landmark due to no possible POI near a decision point. In these situations, an adequate object was chosen in regards to similar criteria as the ones of the algorithm in-situ.

[1]After the revision process, navigation instructions were built in German language by analogy to Rousell and Zipf (2017) as can be seen by the following example (translation: *Turn left at the pharmacy*):

General structure	Imperative to turn	landmark	direction of turn
Example in German	*Biegen Sie bei*	*der Apotheke*	*links ab.*

The last instruction on a route always included the direction to go straight ahead to the destination in the following scheme (translation: *Go to your destination: grocery store*):

General structure	Imperative	destination
Example in German	*Gehen Sie bis zu Ihrem Ziel:*	*Lebensmittelgeschäft*

The resulting route instructions were synthesized using *Google Cloud Text-to-Speech Engine* (Google Inc., 2020).

[1]The navigation instructions were provided exclusively for turning points, a decision which is in line with the idea of spatial chunking (Klippel et al., 2002) and increases ecological validity as the majority of state-of-the-art wayfinding assistance systems provides route instruction also follow this scheme.

Therefore, for a route with K turning points, $K+1$ route instructions were prepared. Figure 2 displays an example of a route with highlighted turning points for which route instructions were constructed and corresponding landmarks referenced in the instructions.

Figure 2: Exemplary route. There are two turning points along the route for which corresponding landmarks were evaluated. In total, three instructions were prepared: Two for the turning points and one last which references the destination. (*background*: OpenStreetMap contributors (2017))

3.2. Procedure

[1]The in-situ study was conducted as an experiment with within-subjects design during which each participant walked two routes: One which the participant drew during the online questionnaire and one that was labeled as unfamiliar to the person. This unfamiliar route was randomly selected from the routes the other participants drew. Figure 3 illustrates this route matching scheme. It was ensured that the participant is unfamiliar with the randomly selected route by checking that it would not lay in or cross areas that were marked as familiar by the participant.

In this work, we will refer to walking one route as a trial. During the in-situ study, participants were equipped with a GNSS receiver (PPM 10-xx38, see figure 4), Bluetooth earphones and a custom-built clicker. In addition to that, head (xSens MTi-300 IMU) and eye movement data (PupilLabs Invisible) was collected but not used in the current study as we wanted to study the impact of those variables which are independent of specific equipment. A sample participant in full equipment is displayed in Figure 4.

Before the start of each trial, the following important explanations and instructions were given to participants:

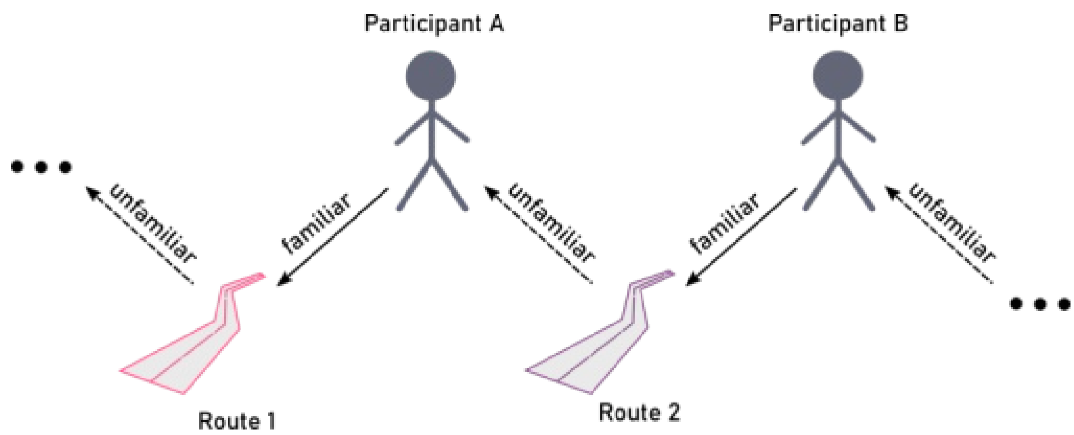

Figure 3: *Route matching scheme.* During the online questionnaire, **Participant A** was asked to draw a route between two familiar places which is **Route 1**. **Participant A** will walk two routes during the study: **Route 1** (trial in **familiar** condition) and **Route 2** which was drawn by **Participant B** (trial in **unfamiliar** condition). Therefore, each route is walked by two participants.

- The landmark-based navigation instructions at turning points were explained by the means of an example which was the same in all trials.
- This example further clarified that route instructions only address turning points. It was emphasized to the participants that the requested navigation instruction might not refer to the upcoming intersection, i.e. the participants would have to continue walking straight ahead until they find the intersection where the instruction can be matched with the environment.
- In the *familiar* condition, the participants were reminded of the destination of the route they had drawn during the online questionnaire but were explicitly asked to follow the route instructions they were given.
- The participants were instructed to request the navigation instructions as often as needed using the custom-built clicking device.
- At the start of the trial, the experimenter pointed participants to the direction in which they should start walking.

Whenever participants requested a route instruction with the custom-built clicking device, a red light lit up in the back of the rucksack (see Figure 4) which was seen by the experimenter who walked behind the participants and played the current instruction on a phone that was connected to the Bluetooth earphones the participant was wearing. This point in time was logged on the experimenter's phone.

Figure 4: **A:** A sample participant in full equipment. **B:** GNSS receiver (PPM 10-xx38).
C: During the experiment, participants requested navigation instructions using a custom-built clicker-device (circled in red) which triggers a LED light located in the backpack informing the experimenter about the request.

4. Analysis

4.1. Problem statement

Before describing the procedure of our analysis, we want to briefly present the problem statements of both models by the means of an example, in analogy to Giannopoulos et al. (2017).

We considered the following scenario: Alice walks from her home to the dentist and uses a navigation system which provides audio instructions. Alice starts walking and approaches an intersection at which she does not know if she has to make a turn. Our models are constructed with the goal of answering the following questions:

Model 1 When will she want to hear the navigation instruction?

Model 2 Will she want to hear the navigation instruction a second time before she makes a turn?

Both models aim to predict two different aspects of a specific behavior. In *Model 1*, the point in time is of interest and *Model 2* yields a binary decision.

4.2. Data preprocessing

[1]Experiments were conducted between June and October 2020. Participants were acquired through personal contact, posts on social media platforms and leaflets; they were reimbursed through lottery. Overall, $N_r = 71$ people registered on our website and, of these, $N_p = 52$ persons (female: 25 , male: 27 , $M_{age} = 26.2$, $Median_{age} = 24$) completed both experiment parts. This results in an overall number of $N = 104$ trials. Applying a case-wise deletion approach, we had to exclude 18 trials, e.g., due to data loss by equipment malfunction. This leads to a final number of $N = 86$ trials to be included in the further analysis.

Figure 5 illustrates an overview of the overall preprocessing procedure.

[1]The goal was to obtain features of five categories: ***r**oute*, ***p**articipant*, ***e**nvironmental*, ***t**rial* and ***b**ehavioral* level. This decision is inline with prior work on wayfinding decision situation by (Giannopoulos et al., 2014), which provides theoretical explanations and empirical evidence that these variables have an impact on the perceived difficulty of a decision situation. These aspects are, hence, likely to have an impact on timing.

4.2.1. Segmentation of Data

For each trial, obtained GPS data which consists of a position measurement at intervals of one second and logged times of navigation requests was processed. By synchronizing the time of both data sets, it was possible to refer the request of a navigation instruction to a position. Then, it was important to obtain meaningful segments of the route. Therefore, a segmentation procedure was performed based on the GPS track and information was obtained in the form of the illustration in Figure 6.

After obtaining a partitioned route, it was important to refer the position of the request to a segment in a reasonable way.

[1]Figure 7 provides an overview of the further segmentation algorithm which was based on OpenStreetMap (OSM) data. Black circles represent the location of inter-

sections according to OSM; the smoothed GPS track of a trial is given in blue, the yellow circles represent the projection of the intersections on this line and the locations at which a participant requested a route instruction are given as green circles. It is important to note that we found segments based on the actual user behavior instead of using the mere distance between two intersections, i.e., subsequent yellow circles. This decision is based on the fact that due to the structure of the environment not all intersections may be perceived as decision points by pedestrians. Each segment starts at a major route point, i.e., either at the starting point or at an intersection to which the previous route instruction referred to. A segment ends at the first intersection along the route after a participant has requested a route instruction for the first time.

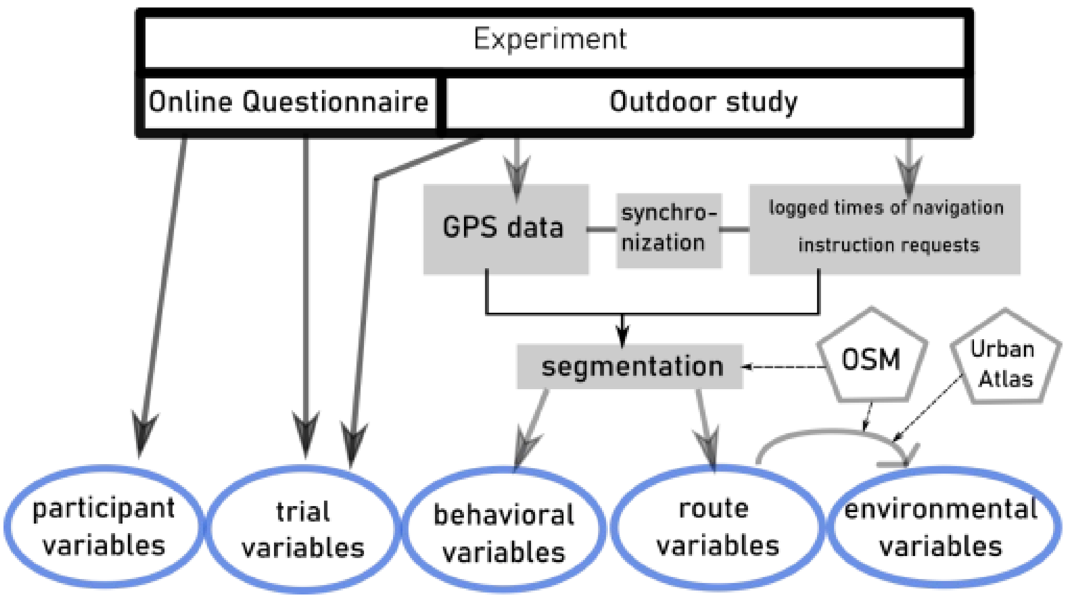

Figure 5: Preprocessing procedure. During the outdoor study, GPS data was measured and the points in time logged at which instructions were requested. A position was assigned to each request through time synchronization between the two measurements. A segmentation algorithm was applied based on OSM data to yield *behavioral* and *route* variables. Using OSM data and data retrieved from the Urban Atlas, *environmental* variables were computed. *Participant* and *trial* variables were obtained from questionnaires during the online questionnaire and information of outdoor study.

This procedure yielded $N_{iseg} = 314$ segments. Segments on which the experimenter had to play the instruction because of the participant missing the turning point were excluded, which resulted in a final number of $N_{seg} = 304$ for further processing.

At this point, we want to introduce some terminology that we will use throughout the work: The starting point of a route, the destination and turning points will be referred to as *major route points*. Between *major route points*, due to multiple intersection, multiple segments can exist. When we address the combination of all segments between two major route points, we refer to it as a *united segment* (see Figure 8).

4.2.2. Retrieval of variables

Participant and ***trial*** variables were obtained during the online questionnaire (see Figure 5). *Participant* variables encompass the information given on demographic data (age, gender, etc.), preferences on spatial ability measures using FRS scale (Münzer & Hölscher, 2011) and personality trait scores based on the results of from BFI-10 questionnaire (Rammstedt et al., 2012).

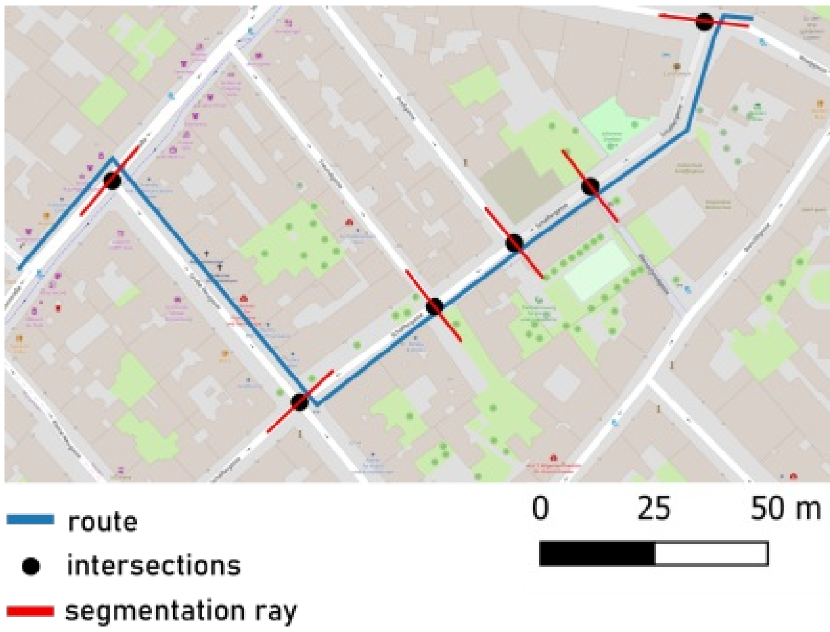

Figure 6: Segmentation process 1. The aim of the segmentation is to partition the route at intersections which are retrieved from OpenStreetMap contributors (2017). The algorithm creates so-called *slicing segmentation rays* which "cut" the route into segments (*background*: OpenStreetMap contributors (2017)).

[1]The reason to choose the FRS scale instead of the Santa Barbara Sense of Direction Scale (Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002) is based on the assumption that preferences/abilities for different spatial strategies (global/egocentric or allocentric as well as the knowledge of cardinal direction) may provide a means to further explain timing results: For example, participants with better egocentric abilities may prefer, e.g., later points in time than people with good allocentric orientation do.

Trial variables included features about a trial such as total duration of the experiment, weekday, time and similar, and most importantly, whether the participant was walking a familiar or unfamiliar route.

We calculated *route* features based on the obtained segments and united segments.

[1]They comprise aspects relating to the route itself, e.g., the length of each route segment, the type of each intersection, information on landmark visibility and so on.

From these route features, environmental variables were derived. Figure 9 exemplifies the retrieval of environmental data for a route segment.

Two main types of environmental variables were considered: The first one was point density of POIs based on OSM data. This was obtained by drawing a 30m buffer around a segment, counting points that lied within this buffer and normalizing it by the length of the segment. The value of the buffer size was set carefully by testing it on segments laying in streets of varying road width with the aim to draw a buffer big enough to contain all POIs that would be visible for the participant traveling on this segment.

As POIs in OSM have tags describing properties of the POI (e.g. a fast food restaurant is typically tagged with tag *amenity* and corresponding value *fast_food*), we decided to also calculate POI densities for POI with specific tags and values, following the POI definition of *POI display* (2013).

The second type of environmental variables was related to landcover classes. Therefore, landcover polygons retrieved from (European Comission, 2012) were used. For this, buffers with the radius of 50m were drawn around a segment. We evaluated which landcover polygons intersect the buffer and calculated the share of buffer area for each

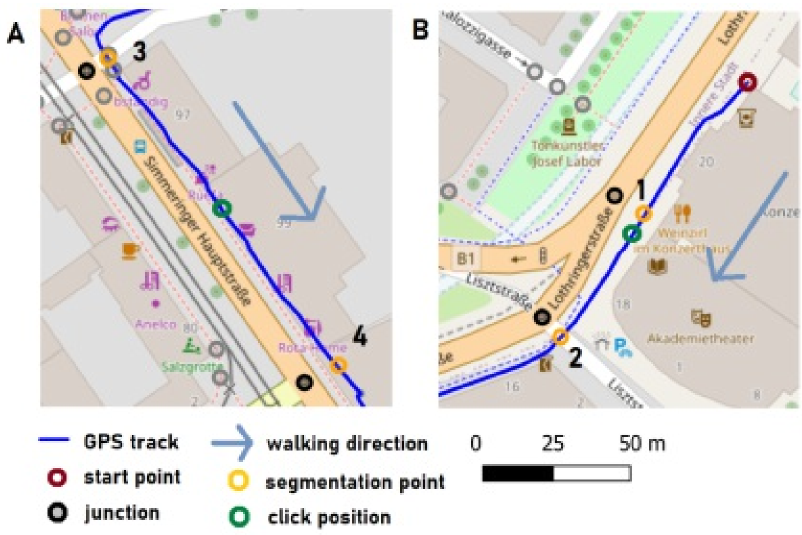

Figure 7: Segmentation process 2. Two possible situations: **A** (regular case): The segment starts at the last turning point denoted as *3*. The first intersection after the click position is denoted as *4* and the segment ends at this intersection. **B**: A route segment covering the distance from the starting point to intersection *2*. Intersection *1* is ignored because the instruction is requested after it was passed, i.e., the participant has not perceived it as a decision point.(*background*: OpenStreetMap contributors (2017), graphic adopted from Golab et al. (n.d.))

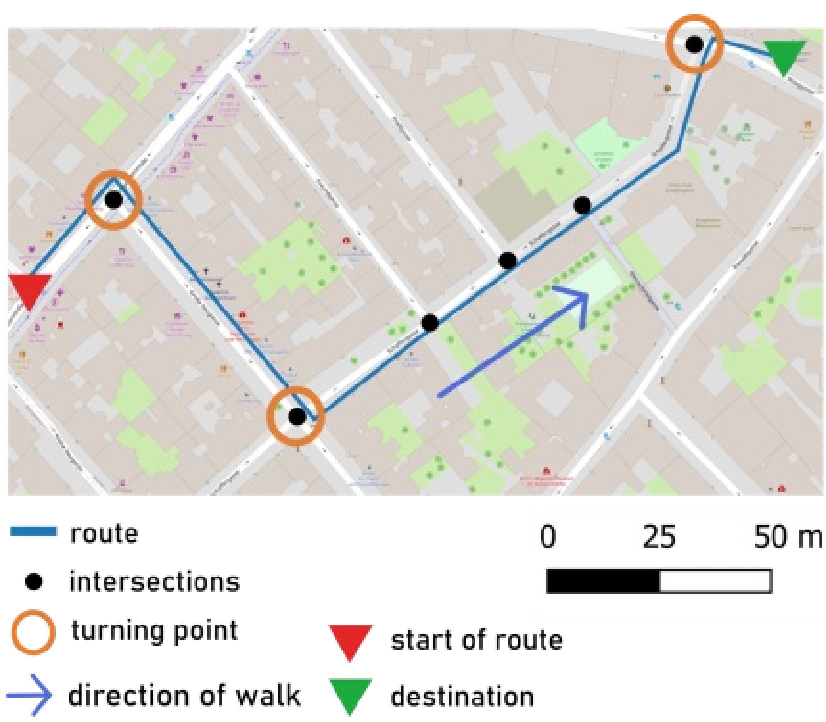

Figure 8: Explaining terminology. The starting point of a route (*red triangle*), turning points (*orange circles*) and destination (*green triangle*) are called **major route points**. Within each pair of major route points, multiple segments can lie. All these segments are merged together and referred to as **united segment**.(*background*: OpenStreetMap contributors (2017))

landcover class as defined by European Comission (2012). The used buffer was bigger for this environmental variable because we were not only interest encompassing what a participant might see but more about the kind of environment the person is traveling in, e.g. whether it is a densely built environment (see Figure 9 for graphical explanation).

[1]Finally, the *behavioral* class encompasses all features relating to the requests of route instructions by participants (e.g., of course, the point in time of the click itself,

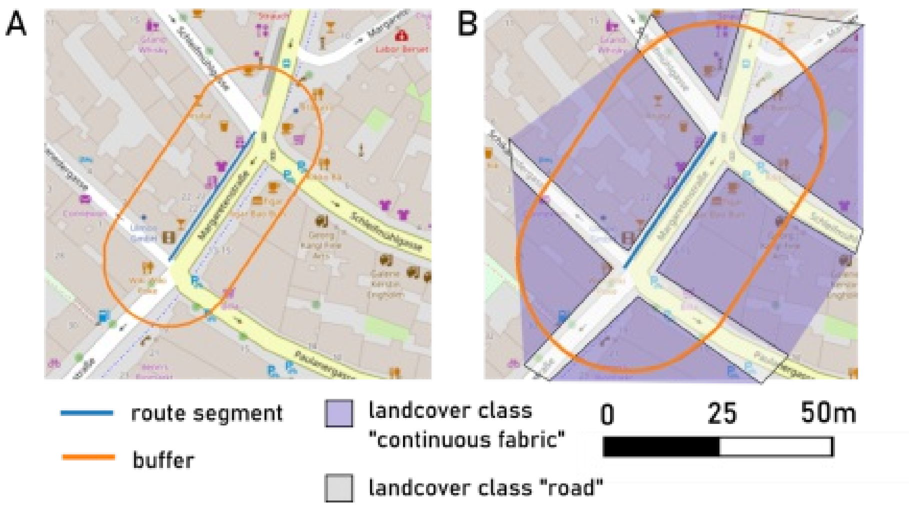

Figure 9: Retrieval of environment variables. **A**: Retrieval of point density values: A buffer with a radius of 30m is drawn around a route segment. In this example, the overall POI density would be 0.29 and point density of POIs with tag *shop* 0.07. **B**: Retrieval of land cover shares: A 50m-buffer is drawn around a route segment. In this example, the predominant class corresponds to continuous fabric (designated as *LC_11100* by European Comission (2012)). Therefore, the calculated value landcover share of this class would be about 0.8 and 0.2 for the landcover class implying roads (*LC_12220*).

but also aspects such as the distances to the previous and upcoming intersections etc.).

4.3. Data analysis

The aim of this analysis was to identify significant variables in the observed behavioral processes and further to draw conclusions about possible explanations based on their magnitude, direction of impact and significance. This can be achieved by using a regression model which allows stating causal relationships between independent variables and a dependent variable.

The two research questions addressed in this work call for two different analysis approaches as one is directed towards the prediction of a point in time and the other one can be expressed by the means of a binomial classification. While choosing analysis methods, the fact that our data holds multiple observations per subject had to be regarded. A possible correlation within data points acquired from one subject was assumed. For the prediction regarding *when* a person would want to hear a navigation instruction, the survival analysis was chosen. Although, this model assumes independence between all observations, the sandwich estimator can be applied to compensate for possible correlation within the outcome (e.g. Liu, 2014; Shaffer & Hiriote, 2009). For the second research question, the Generalized Estimating Equations model which solves a marginal model and estimates within-subject correlation was used (Liu, 2015).

4.3.1. Survival Analysis Model

[1]Driven mainly by advances in the biomedicine domain, a family of models called *survival analysis models* have been proposed (see Hosmer Jr, Lemeshow, & May, 2011; Kalbfleisch & Prentice, 2011, for a detailed overview); these show methodological and conceptual advantages over traditional regression approaches (see, e.g., Bhat & Pinjari, 2007). In brief, these models perceive duration as a survival process and center their focus on the share of individuals that survive past a given (time) point. A focal element

of those models revolves around the notion of hazard, i.e., the rate at which the duration process changes over time.

[1]The application of survival analysis models in spatial settings was explored and exemplified for the first time by Waldorf (2003). A number of applications have built upon that work and utilized such models for tackling distance-related questions such as trip length modeling (see, e.g., Anastasopoulos, Islam, Perperidou, & Karlaftis, 2012; Sarlas & Axhausen, 2018).

[1]Among those models and for cases which focus primarily on prediction, choosing fully parametric models is most appropriate as these fully describe the basic underlying survival distribution and, at the same time, quantify how this distribution changes as a function of the explanatory variables (Hosmer Jr et al., 2011). Two categories of such models exist, namely the proportional hazard and the accelerated failure time (AFT) models. These differ with respect to the assumptions of how the survival function is affected by the explanatory variables. While the former assume that the explanatory variables have a constant multiplicative effect on the underlying hazard function, this relationship is assumed to be also multiplicative on the time scale by the latter.

[1]By analogy with Giannopoulos et al. (2017), we focus exclusively on estimating an AFT model as it is reasonable to assume that the relationship of the explanatory variables is multiplicative on time. T represents the timing or distance of instructions for an individual with a cumulative distribution function $F(t) = Pr(T \leq t)$. The survival function represents the probability of observing a survival distance higher than t, denoted as $S(t) = \Pr(T > t) = 1 - F(t)$. Subsequently, the hazard function, defined as the probability of a process ending at point t given that it has lasted up to point t, is as follows:

$$h(t) = \frac{\mathrm{f}(\mathrm{t})}{S(t)} \tag{1}$$

[1]Essentially, the knowledge of either function (i.e., $f(t)$, $F(t)$, or $h(t)$) allows the direct inference of the remaining two. In case of the AFT models with a Weibull survival function, T is defined as $T = e^{\beta_0 + \beta_i x} * \varepsilon$, with β's representing the effect of explanatory variables x_i, and an error component ε.

[1]Applying a log transformation results in:

$$ln(T) = \beta_0 + \beta_i x_i + \sigma * \varepsilon^* \tag{2}$$

with $\varepsilon^* = ln(\varepsilon)$ following the extreme minimum value distribution, denoted as $G(0, \sigma)$ with σ being the scale parameter. The corresponding hazard and the survival function are:

$$h(t, \chi_i, \beta_i, \lambda) = \frac{\lambda t^{\lambda-1}}{\left(e^{\beta_0 + \beta_i x_i}\right)^{\lambda}} = \lambda t^{\lambda-1} e^{-\lambda(\beta_0 + \beta_i x_i)} = \lambda\gamma\left(te^{-\beta_i x_i}\right)^{\lambda-1} e^{-\beta_i x_i} \tag{3}$$

$$S(t, \chi_i, \beta_i, \sigma) = exp\{-t^{\lambda} exp[(-1/\sigma)(\beta_0 + \beta_i x_i)]\ \} \tag{4}$$

with$\lambda = 1/\sigma$ *and* $\gamma = exp(-\beta_0/\sigma\ )$. With this formulation, the equation for the median survival time can be derived by setting $S = 0.50$:

$$t_{50}(\chi_i, \beta_i, \sigma) = [-ln(0.5)]^{\sigma} e^{\beta_0 + \beta_i x_i} \tag{5}$$

[1]Formula (2) shows that the β's quantify the effect of the explanatory variables on T, which can, for this case, be interpreted as semi-elasticity values, i.e., 100*β_i is the approximate percentage change on T for a unit change on x_i. However, that change is not constant along the corresponding survival function (see 4). Based on formula (5), the impact of a change on x_i on its median T is given by:

$$TR\left(x_i, x_i'\right) = \frac{t_{50}\left(x_i', \beta_i, \sigma\right)}{t_{50}\left(x_i, \beta_i, \sigma\right)} = \frac{\left[-ln\left(0.5\right)\right]^{\sigma} e^{\beta_0+\beta_i x_i'}}{\left[-ln\left(0.5\right)\right]^{\sigma} e^{\beta_0+\beta_i x_i}} = e^{\beta_1 \Delta x_i} \tag{6}$$

4.3.2. Generalized Estimating Equations

The Generalized Estimating Equations (GEE) model was introduced by Liang and Zeger (1986) and Zeger and Liang (1986) as an extension of Generalized Linear Models (GLM) (Nelder & Wedderburn, 1992) to account for correlations in observations in the estimation of GLM coefficients. GEE is designed to model population-average effects of covariates and is therefore frequently used in the fields of medicine and sociology (Pekár & Brabec, 2018).

Coefficient estimates are calculated using quasi-likelihood which requires the specification of relations between the mean outcome and covariates, and between the variance of the outcome and mean of the outcome. The mean model μ_i of a dependent variable y_i for subject i is expressed by

$$f(\mu_i) = \mathbf{x}_i\beta \tag{7}$$

where $\mathbf{x}_i$ is a vector of the independent-variable observations and β a vector of covariates of length $p+1$ for p independent features. $f(.)$ denotes the so-called *link* function which is analogous to link functions for GLM and allows fitting GEE for various distributions of outcome variable(Ballinger, 2004). The relation between variance of a outcome υ_i and the mean outcome is given as $\upsilon_i = g(\mu_i)/\Phi$, Φ being a scaling parameter and $g(.)$ a known variance function. For N_i observations of p independent variables per subject, we define the quasi-likelihood relations by:

$$f(\mu_{ij}) = \mathbf{X}_{ij}^T\boldsymbol{\beta} \tag{8}$$

and

$$\mathbf{V}_i = \frac{\mathbf{A}_i^{1/2}\mathbf{R}_i(\boldsymbol{\alpha})\mathbf{A}_i^{1/2}}{\Phi} \tag{9}$$

A_i is a diagonal matrix of shape $(N_i \times N_i)$ with $g(\mu_{ij})$, $j = 1, ...N_i$, as its diagonal elements. $\mathbf{R}_i(\boldsymbol{\alpha})$ is called the "working" correlation matrix and $\boldsymbol{\alpha}$ is a vector of its elements. The working correlation matrix represents the correlations of outcomes within a subject, and its structure can be individually determined (Pekár & Brabec, 2018). Pekár and Brabec (2018) give a thorough overview on most common structures of $\mathbf{R}_i(\boldsymbol{\alpha})$ and the underlying assumptions that are made by choosing one.

Estimates of $\boldsymbol{\beta}$ are yielded by solving the following formula for M subjects:

$$U(\boldsymbol{\beta}) = \sum_{i=1}^{M} \left(\frac{\delta\boldsymbol{\mu}_i}{\delta\boldsymbol{\beta}}\right)^T \mathbf{V}_i^{-1}\left(\mathbf{y}_i - \boldsymbol{\mu}_i\right) = 0 \tag{10}$$

This estimating equation depends on the unknown $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$.

Zeger and Liang (1986) suggested an iterative approach to obtain estimates for $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$ and Φ. By introducing a sandwich estimator, the covariance matrix of $\boldsymbol{\beta}$ is expressed by:

$$\mathbf{V}_\beta = \lim_{M\to\infty} M \left[\sum_{i=1}^{M} \left(\frac{\delta\boldsymbol{\mu}_i}{\delta\boldsymbol{\beta}}\right)^T \mathbf{V}_i^{-1} \left(\frac{\delta\boldsymbol{\mu}_i}{\delta\boldsymbol{\beta}}\right)\right]^{-1} \mathbf{E}_\beta \left[\sum_{i=1}^{M} \left(\frac{\delta\boldsymbol{\mu}_i}{\delta\boldsymbol{\beta}}\right)^T \mathbf{V}_i^{-1} \left(\frac{\delta\boldsymbol{\mu}_i}{\delta\boldsymbol{\beta}}\right)\right]^{-1} \tag{11}$$

with

$$\mathbf{E}_\beta = \left[\left(\frac{\delta\boldsymbol{\mu}_i}{\delta\boldsymbol{\beta}}\right)^T \mathbf{V}_i^{-1} Cov(\mathbf{y}_i)\mathbf{V}_i^{-1} \left(\frac{\delta\boldsymbol{\mu}_i}{\delta\boldsymbol{\beta}}\right)\right] \tag{12}$$

The definition of $\mathbf{V}_\beta$ was obtained by assuming that GEE yields asymptotically consistent $\hat{\boldsymbol{\beta}}$ for a zero mean of the true $\boldsymbol{\beta}$ values under mild regularity conditions (Liang & Zeger, 1986). With an initial guess for unknown parameters in Formula 9, $\hat{\boldsymbol{\alpha}}$ and $\hat{\Phi}$, the first estimate $\hat{\boldsymbol{\beta}}$ is yielded using formula 10 which is again used to estimate a new set of $(\hat{\boldsymbol{\alpha}}, \hat{\Phi})$ until convergence (Hilbe & Hardin, 2008).

$\boldsymbol{\alpha}$ and Φ are consistently estimated through the standardized residuals $r_{ij} = (y_{ij} - \hat{\mu}_{ij})/\sqrt{\upsilon_{ij}}$, where $\hat{\mu}_{ij}$ based on the current $\hat{\boldsymbol{\beta}}$. $Cov(\mathbf{y}_i)$ is obtained by multiplying the residual vectors for observations of a subject, $\mathbf{r_i}\mathbf{r_i}^T$ (Liang & Zeger, 1986; M. Wang, n.d.).

For solving the binary-classification task at hand, the logit link function was chosen in analogy to a classic logistic regression (Liu, 2015). Therefore, we define our binary response as follows:

$$logit(\mu_{ij}) = log\frac{Pr(y_{ij} = 1)}{Pr(y_{ij} = 0)} = \mathbf{X}_{ij}^T\boldsymbol{\beta} \tag{13}$$

We further chose the "exchangeable" working correlation structure which specifies constant correlation among observations stemming from the same subject with the assumption that the preference to hear a route instruction would be subject-specific (Pekár & Brabec, 2018). This defines for subject i by:

$$\mathbf{R}_i(\boldsymbol{\alpha}) = \begin{pmatrix} 1 & \alpha & \alpha & \cdots & \alpha \\ \alpha & 1 & \alpha & \cdots & \alpha \\ \alpha & \alpha & 1 & \cdots & \alpha \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha & \alpha & \alpha & \cdots & 1 \end{pmatrix} \tag{14}$$

5. Results

In the model building process, state-of-the-art methodology was applied: Initial model fitting of all available variables was conducted to identify influential ones (suggested by e.g. Hosmer Jr, Lemeshow, & Sturdivant, 2013, in the context of logistic regression). To ensure absence of distortion due to multi-collinearity, it was tested whether the variance inflation factors (VIF) of all variables in the model had values < 5 (Akinwande, Dikko, Samson, et al., 2015). The number of variables in the model was further reduced by observing their p-values, their impact on p-values and changes in coefficients of the other independent variables in the model and their effect on the information criterion which was the Akaike Information Criterion (AIC) in case of the survival analysis (Akaike, 1973) and Quasi-likelihood Information Criterion (QIC) in the model building process of the GEE (Pan, 2001). AIC and QIC are based on information theory and assist in the model selection by summarizing goodness of fit and complexity by one measure. In addition to that, the model's robustness was ensured by sequential removal of influential data points and simultaneous observation on the change of estimated coefficients. Moreover, during the AFT analysis, a robust sandwich estimator was applied in the calculation of model parameters to make up for possible correlation within the outcome.

[2]Tables 3 and 6 display parameters of the final models, their standard errors, corresponding p-values based on Wald statistic and goodness of fit measures. Though the coefficient values satisfy different models, we can make similar assumptions on its effect on the corresponding dependent variable based on their magnitude and sign. It is important to note that the size of the coefficients depends on the range of values of the features and they have to be interpreted ceteric paribus, i.e. the estimated parameter values how an impact of the variable as if the other are kept constant. A variable is classified as significant when its p-value is below 5%.

5.1. *Model 1: Asking for an instruction for the first time after a turn*

[2]Figure 10 illustrates the observation that we want to predict: The person has made a turn or just started walking and does not know whether a turn has to be made at the upcoming intersection. Along this route segment, the person has to, therefore, request the instruction at some point before passing the upcoming intersection. The participants were allowed to trigger a request multiple times. In this model, though, we are explicitly interested in the first request. Before applying AFT model, further data cleaning procedures were conducted: Observations of participants in familiar condition that were able to see the destination from the position of the instruction request (25 cases) were excluded as we could assume that as soon as participants would see the familiar destination, they would not need the instruction for assistance in wayfinding anymore. Furthermore, cases in which the first request was made before entering the segment (35 cases) had to be removed from the data because this could not be processed in survival analysis. These were always first segments of 245 unitied segments (see Figure 10). Environmental variables where retrieved based on the geometry segments of interest illustrated in Figure 10 using methodology described in Section 4.2.2.

[1]The request on a segment has a temporal and spatial dimension. We are naturally

Figure 10: **Model 1**: A person has just turned, approaches the upcoming intersection and requests the instructions for the first time at the position marked by the green cross. Our analysis aimed to predict the distance between the position of the *green* cross and the upcoming intersection (*red* circle) which is normalized by the length of the route segment (marked as *black* line).
Model 2: The navigation instructions are exclusively for turning points and the announcement of the destination and are played as many times as a person wants to. In model 2, the focus was on classifying whether someone would want to hear a navigation instruction more than once, based on personal, environmental, route, trial and behavioral variables of the first request. We are further not only interested in the segment on which the first request is made but the features of the united segment (*black* line) between the past and the upcoming turning point. In the displayed example, the route instruction is requested a second time at the position of the *grey* cross.
Backgrounds: OpenStreetMap contributors (2017)

bound to the length of the segment and therefore chose to focus sorely on the spatial dimension. The positions of first requests were normalized to a range $[0, 1]$ by dividing by segment length, in order to have a uniform duration period for all observations which is a prerequisite for the model estimation as follows.

[1]Subsequently, an AFT model is estimated with a Weibull duration distribution in place, similarly to the one presented in formula (4). The calculations were conducted using the open-source statistical software R (Core Team et al., 2013), exploiting version 3.2-7 of the *Survival* package (Therneau, 2014). The results of the AFT model parameter estimation along with the accompanied goodness of fit measures, are presented in Table 3 , while descriptive statistics of the employed sample are given in Table 2 .

[1]Obtaining estimates for β allows us to estimate the survival and hazard functions (see formulas 3 and 4) for different sets of explanatory variables, and, hence, individuals

and spatial environments. Parameter interpretation can take place both in terms of sign and magnitude: An estimate with a positive sign implies a longer survival (i.e., instructions will be required at a later point in time), while a negative sign means the opposite. Concerning the magnitude, a quantitative interpretation can be made based on formulas (2) and (6). Based on the estimated parameters, we can obtain point estimates of quantiles of the distribution (e.g., the median) which are of potential interest for predicting the point in time at which a system should automatically present a route instruction.

[1]The obtained estimates indicate that participants requested a route instruction later as a function of their age (variable *age_gt_40*) and on segments longer than 120m if they belong to the group of people whose factor score for preference for egocentric orientation is below 3 (variable *EGO_lt_three*lngSegm*). All remaining variables describe an earlier request for an instruction: This holds for the two different classes of landcover (variables *LC_1* and *LC_2*) which are rendered significant at the 5% level, as well as for people scoring below average on the personality factor *openness* (variable *BFI_o_low*). In addition to that, if participants walk on long segments in an area they are unfamiliar with (variable *unfamiliar*lngSegm*), they request a route instruction earlier. Finally, sense of direction and familiarity interact with each other, i.e., depending on their sense of direction, wayfinders want route instructions earlier on familiar (variable *SOD*familiar*) and even more earlier on unfamiliar settings (variable *SOD*unfamiliar*). Figures 11, 12 and 13 provide further elaboration and interpretation of the model results:

[1]In Figure 11, the median predictions (calculated based on Formula 5) for the observations used for the model estimation are plotted against the actual ones. A strongly positive relationship between the two seems to be in place while their correlation is found to be equal to $\rho = 0.45$.

[1]In Figure 12, empirical survival results are compared against predicted ones for two common cases identified in our sample having the following characteristics: $BFI\_o\_low = 1$, $lngSegm = 1$, and $age\_gt\_40 = 0$, i.e., people who are below 40 years of age, having a below average degree of openness and walk on long segments. The empirical survival function of those observations that correspond to a familiar setting are presented on the left, whereas the unfamiliar setting is shown on the right. The predicted mean survival functions have been obtained by making use of the estimated parameters and inserting the mean of the remaining explanatory variables into formula (4), with the exception of dichotomous variable *EGO_lt_three* which is set to 1. The figure illustrates that in both cases, the predicted mean survival rates are very close to the empirical ones while their 95% confidence interval values are always overlapping.

[1]Finally, the impact of the different explanatory variables on the predicted survival rates is demonstrated by modifying those variables accordingly, and plotting the resulting survival rates per case (Fig. 13). For that reason an artificial observation resembling a wayfinder with the following characteristics is defined as a base case, while for the remaining continuous variables the mean values of the sample are used (Table 2): $BFI\_o\_low = 0$, $lngSegm = 0$, $age\_gt\_40 = 0$, $EGO\_lt\_three = 0$, $unfamiliar = 1$, i.e. a person of less than 40 years of age, with a below average openness and very high preference for egocentric orientation, who walks on unfamiliar segments which are no longer than 120m. The modification on the dummy variables

consists of setting them to 1 (i.e. considering above average openness, long segments, older people, high preference for egocentric orientation or familiar segments); the continuous variables are modified by adding/subtracting a value equal to the respective standard deviation. On the left-hand side of the figure, the environmental and route characteristics of the base case are modified while on the right-hand side, the trial and personal ones are changed (see Table 1 for an explanation which variables these are). For instance, the black dotted line on the left side of the figure resembles the baseline artificial observation with an increase only in *LC_1*. Similarly, the red line resembles the baseline artificial observation with an increase only in *LC_2*. The blue line resembles the baseline artificial observation with a change from $lngSegm = 0$ to $lngSegm = 1$, indicating that the wayfinder is walking on a long segment. In all of these three cases, the time that the wayfinder would ask for instructions decreases. As it can be seen, the most influential explanatory variables appear to be length of segment (*lngSegm*) along with the below average degree of openness (*BFI_o_low*).

Table 1: Influential variables in **Model 1**. **levels:** *P*: participant, *R*: route, *T*: trial, *E*: environment
sources: *OQ*: online questionnaire that was completed by participants, *UA*: *Open Street Map,OSM*: OSM. (adopted from Golab et al. (n.d.))

level	variable	description	type	unit	source
P	age_gt_40	age greater than 40	dichotomous	N/A	OQ
	BFI_o_low	result of subscale openness of BFI-10 scale; threshold <3.41 according to norm data (Rammstedt et al. 2012)	5-point likert scale	N/A	OQ
	SOD	sense of direction derived from FRS questionnaire	7-point likert scale	N/A	OQ
	EGO_lt_three	factor EGO derived from FRS questionnaire	7-point likert scale	N/A	OQ
R	lngSegm	segment length >120m This threshold was found empirically, i.e. evaluated based on lower and upper quartile of the segment length and different thresholds were tested to classify short and long segments, respectively. However, only long segments yielded a significant effect.	metric	meter	
T	familiar/unfamiliar	participant is familiar/unfamiliar with route and environment	dichotomous	N/A	OQ
E	LC_*	land cover share of 50m buffer around route segment 1 = 12100; 2 = 1110 + 11210 12100, 1110, 11210 ... landcover codes of Urban Atlas (European Comission 2012)	metric	N/A	UA
DV	distance norm.	of navigation request to upcoming intersection normalized by segment length	metric	N/A	

Table 2: Summary statistics of the observations used for AFT model estimation. *(d)* denotes a dichotomous variable; for these variables column mean represents the proportion in the sample. Variable names are explained in Table 1.(adopted from Golab et al. (n.d.))

Statistic	Mean	St. Dev.	Min	Max
distance norm.	0.494	0.333	0.004	1.000
segment length	80.794	58.600	4.516	426.500
length_long (d)	0.143	-	-	-
age	26.596	9.001	18	59
age_gt_40 (d)	0.073	-	-	-
LC_1	0.129	0.179	0	1
LC_2	0.427	0.287	0.000	0.900
LC_3	0.090	0.214	0	1
familiar (d)	0.420	-	-	-
unfamiliar (d)	0.580	-	-	-
SOD	4.822	1.468	1.920	6.911
EGO	3.595	1.099	0.478	6.216
EGO_lt_three (d)	0.314	-	-	-
BFI_o	3.520	1.074	2	5
BFI_o_low (d)	0.424	-	-	-

Table 3: Parameters and goodness of fit measures of AFT model for normalized timing of instructions based on the AFT model. Coefficients β and scale parameter σ correspond to definitions by formulas in chapter 4.3.1.(adopted from Golab et al. (n.d.))

Variable	β	Robust std. error
age_gt_40	0.709***	0.173
LC_1	-0.541*	0.224
LC_2	-0.524***	0.138
LC_3	-0.352^{+}	0.184
BFI_o_low	-0.293*	0.121
unfamiliar*lngSegm	-0.712*	0.298
SOD*familiar	-0.046*	0.020
SOD*unfamiliar	-0.058**	0.018
EGO_lt_three*lngSegm	0.593**	0.205
Log(scale)	-0.314***	0.078
Scale σ	0.73	
Observations	245	
LogLikelihood	-43.5	
LogLikelihood (intercept only)	-62	
AIC	106.97	

p value: + $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

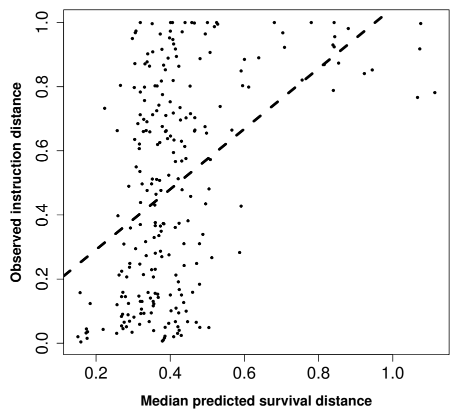

Figure 11: Predicted median survival values based on the estimated AFT model, compared against the observed ones. (adopted from Golab et al. (n.d.))

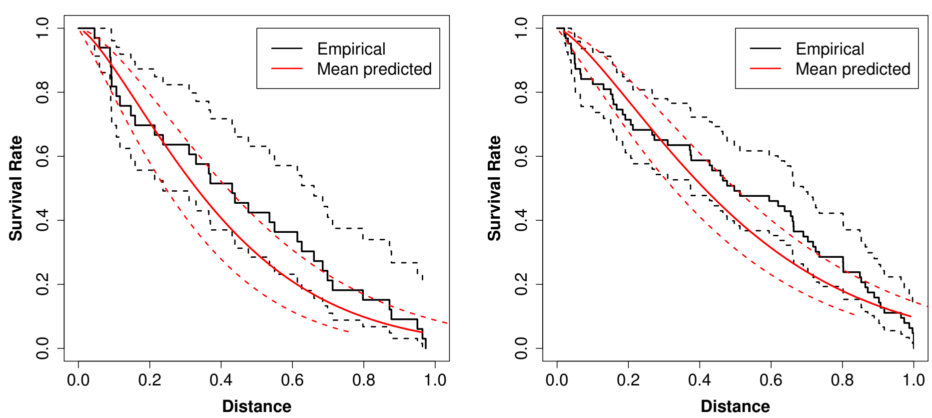

Figure 12: Empirical survival rates for two given subsets of observations (left: familiar, right: unfamiliar segments), compared against the mean predicted ones. Dotted lines represent the 95% confidence interval values. (adopted from Golab et al. (n.d.))

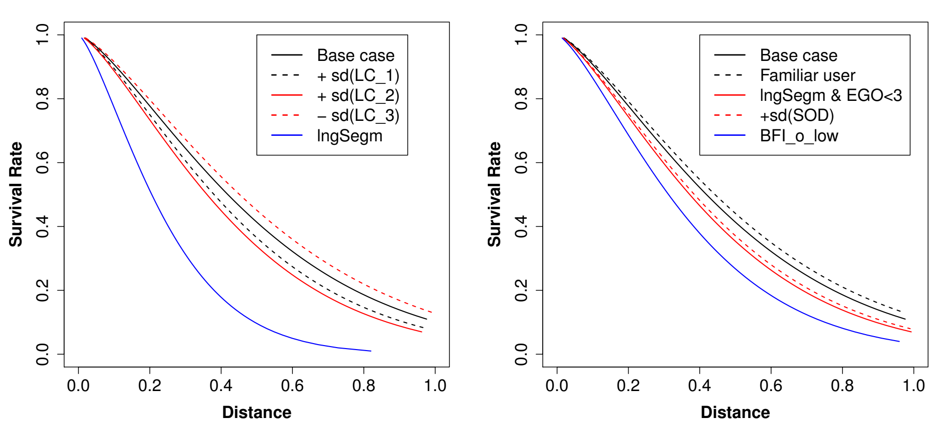

Figure 13: Variation of survival rate predictions due to explanatory variables modifications. The corresponding modifications are applied to a base case scenario in the following manner: continuous variables=± 1 standard deviation, dummy variables=1. (adopted from Golab et al. (n.d.))

5.2. Model 2: Asking for an instruction multiple times

In the experiment setup, participants were allowed to request a navigation instruction as often as they wanted. In 29.9% of the total cases (91 out of 304), participants requested an instruction for at least a second time. The aim of the second model was to predict whether a person would want to hear a navigation instruction a second time. Besides personal, trial and route variables, an observation comprises behavioral data describing the position of the first request and environmental data calculated based on a *united* segment (for explanation of this term see Section 4.2.1 and Figure 10 for an example). To formulate a binary classification, an observation was labeled 0 if a navigation instruction was requested only once and 1 if it was requested for at least a second time.

Within our data, observations also include last united segments of routes. The difference to other united segments is that along the last ones the navigation instructions announce the destination. These are not navigation instructions in the traditional sense (see Section 3 for syntax) as they do not included an imperative to turn. To observe whether this effects the behavior of the wayfinder differently, a dichotomous variable that labeled these observations was introduced.

During the model building process, it became evident that POI density variables would be significant in the model. After suspecting overfitting, the variables were further inspected and it was recognized that many of the point density variables had value 0 for most of the observations. Furthermore, we realized that the point density variables cannot be all treated as independent between each other as multiple tags can be assigned to an object in OSM and therefore, the presence of one tag might depend on the presence of another. For example, there are some coffee places in Austria that are tagged with *amenity:cafe* and *shop:coffee*. Therefore, POI density variables of only one tag were chosen to be used in the analysis. Based on criteria such as frequency of occurrence and significance in the model, we decided to use only POI variables of tag *amenity*. To tackle the issue of overfitting and to keep classification among objects with this tag, the different possible values of tag *amenity* in our data were collected and a grouping of them was carefully conducted based on their appearance and what the objects are used for. This led to six deduced variables describing point density: *amenity_gastronomy*, *street_furniture*, *amenity_mobility*, *amenity_education*, *amenity_health*, *amenity_culture*. The precise definition of them can be found in Section E.

The GEE model with logit link function was applied using `R` version 4.0.3 and functionalities of the *geepack* (Halekoh, Højsgaard, Yan, et al., 2006). Its application models population-average effects as we aimed to solve for the logit of marginal probability which is defined in Formula 13.

Table 6 displays the results of the obtained GEE model. The variable names are explained in Table 4 and corresponding statistics are found in Table 5. Along with the coefficients β which satisfy Formula 13, we obtain parameter α which expresses the correlation between observations within a subject and the scaling parameter which relates the correlation matrix of the mean outcome to the one of the outcomes of observations (see Formula 9).

The estimated GEE model implies that the later a landmark is visible, the higher the chances of an occurrence of a second request increase (*dist_of_landmark_visibility*).

The chances of a second request also increase, when a health facility is present (*amenity_health_present*). The chances decrease with increased density of mobility infrastructure including bike rentals, parking, fuel and charging station and more (see Table 4 for more details). *rel_click_pos_united_segment* is a behavioral variable describing the position of the first request of a route instruction on a united segment. It is the ratio between the distance to the last major route point and the united segment length. An increase of the ratio causes a decrease of the chances that a second request will be made. The chances of occurrence of a second request further increase when a person is on the last united segment and approaching the destination (*last_instr_on_route*). In this model, one interaction term is included: It is an interaction between a behavioral and a dichotomous personal variable (*time_passed_since_start * BFI_n_high*). *BFI_n_high* equals 1 for people with high scores on subscale neuroticism of BFI-scale and 0 for lower (threshold 3.3, derived from Rammstedt et al., 2012). Let t_0 be the start of the experiment and t_N the point in time at which a route instruction is requested for the first time, then *time_passed_since_start* is defined as $t_N - t_0$ in seconds. This term is, therefore, only active for people who score high on the neuroticism subscale of BFI and lower the chances of a second request the more time has passed, since the experiment start t_0 at the moment of the first request t_N.

It is important to note here that the GEE model is a marginal model aimed to observe population-level effects (Pekár and Brabec (2018)). It can therefore not be directly used to make subject-specific predictions as it ignores subject-specific scale and the chosen working correlation structure neglects the possibility of individual correlation parameters within observation clusters. Furthermore, direct population-average predictions are not possible if a non-linear link function is used. For this, a specific retransformation algorithm is needed (Liu, 2015). The model still yields correct estimates on population-level which is often sufficient in behavioral science (Pekár & Brabec, 2018).

Table 4: Influential variables in *Model 2*. **levels:** P: participant, R: route, T: trial, E: environment, DV: dependent variable
sources: OQ: online questionnaire that was completed by participants, OSM: OSM. Readers may want to refer to the supplementary material for further details on these.

level	variable	description	type	unit	source
P	BFI_n_high	result from subscale neuroticism of BFI-10 scale threshold >3.3, calculated based reference values by Rammstedt et al. (2012) of BFI_n scores of all participants	5-point likert scale	N/A	OQ
B	rel_click_pos_united_segment	distance between past major route point and position of first request of route instruction devided by the distance of the united segment	metric	N/A	
	time_passed_since_start	time passed since the start of the navigation at the point in time of the first request	metric	seconds	
R	last_instr_on_route	This variable implies whether the route instruction is the last one on the given route. If it is, the structure of the route instruction is different to the others (see Section 3).	dichotomous	N/A	
	dist_of_landmark_visibility	distance between last major route point and point at which the landmark referenced in the route instruction can be seen for the first time	metric	meter	OSM
T	familiar/unfamiliar	participant is familiar/unfamiliar with the route and the environment	dichotomous	N/A	OQ
E	amenity_mobility	point density of POIs with amenity values bicycle_parking, bicycle_rental, bicycle_repair_station, car_sharing, charging_station, fuel, taxi, parking, parking_entrance, compressed_air	metric	1/meter	OSM
	amenity_health_present	This variable implies whether one of following amenity values is present: dentist, doctors, veterinary, healthcare, pharmacy	dichotomous	N/A	OSM
DV	mutliple_requests	This variable indicates whether multiple requests were made.	dichotomous	N/A	

Table 5: Summary statistics of the observations used for GEE model estimation. *(d)* denotes a dichotomous variable; for these variables column mean represents the proportion in the sample. Variables are described in Table 4.

Statistic	Mean	Std. Dev.	Min	Max
multiple_requests	0.299	-	-	-
distance_of_landmark_visibility	102.213	192.696	0.000	866.533
amenity_mobility	0.015	0.0224	0.000	0.231
rel_click_pos_united_seg	0.237	0.294	0	1
unfamiliar (d)	0.520	-	-	-
last_instr_on_route (d)	0.280	-	-	-
amenity_health	0.002	0.005	0.000	0.055
amenity_health_present (d)	0.329	-	-	-
time_passed_since_start	361.778	39.811	1.392	1077.325
BFI_n	3.090	0.995	1.000	5.000
BFI_n_high (d)	0.141	-	-	-

Table 6: Parameters and goodness of fit measures of final GEE model for binary classification (0 - route instruction is requested once, 1 - route instruciton is requested multiple times). Coefficients β and scale parameter σ correspond to definitions by formulas in chapter 4.3.2. *Number of clusters* is the number of subjects and *Max. cluster size* is the maximum number of observations of a subject.

Variable	β	Std. error
dist_of_landmark_visibility	0.002*	9.12E-04
amenity_mobility	-20.1*	8.78
rel_click_pos_united_seg	-2.45***	0.583
unfamiliar	4.54^{+}	0.279
last_instr_on_route	-1.35***	0.334
amenity_health_present	0.966***	0.270
time_passed_since_start * BFI_n_high	-0.001*	5.81E-04
Scale paramter Φ	0.93	
R parameter α	0.00384; Std.error = 0.168	
Observations	304	
Number of clusters	48	
Max. cluster size	13	
Quasi-Likelihood	-142.74	
Quasi-Likelihood (intercept only)	-186	
QIC	299.98	
p-value: + p <0.1; * p<0.05; ** p <0.01; *** p <0.001		

6. Discussion

Our modeling approach is mostly data-driven as we obtain our models by taking all available variables of different levels (personal, environmental and route level) into consideration and using information criteria and Wald statistic to obtain final models which illustrate the influence of different variables but do not indicate a reason for it. We can, therefore, only make assumptions with caution about why a variable has the given effect. The discussion of variables is divided by their groups for each model.

6.1. Model 1

6.1.1. Environmental variables

[1]According to our model, people request route instructions the earlier for route segments the higher the proportion of land cover classes *LC_1* or *LC_2* is along them. *LC_1* represents the Urban Atlas (European Comission, 2012) class *12100 (Industrial, commercial, public, military and private units)*, whereas, *LC_2* subsumes Urban Atlas classes 11100 and 11210, (European Comission, 2012, p. 9), i.e., it comprises areas of predominantly residential use with a soil sealing of >50%. Both variables show a considerable difference in average area of building footprints (*LC_1:* 1816.73m^2, *LC_2:* 661.55m^2). In urban areas, *LC_1* covers mostly public buildings (e.g., universities, museums) and associated features. *LC_2* shows a medium-sized positive correlation (Spearman's $\rho = 0.56$) with the presence of OSM features tagged as *shop*. However, the density of built-up areas, which we calculated based on OSM building footprints and the extent of landcover class polygons along the route segments is very similar (*LC_1*: 46%; *LC_2*: 50%). This result and the fact that both variables show a negative impact on timing (i.e., the higher the value for *LC_1* and *LC_2* the earlier people would ask for instructions) suggests that the impact of *LC_1* and *LC_2* may stem from similar source. One possible source is a limited line of sight in these environments. For example, crowds in public places are likely to occur in areas with many public buildings or shops. In addition to that, the high density of built-up areas may cause a limited line of sight on upcoming intersections in general. This interpretation is in line with, e.g., research indicating the importance of visibility in advance for landmark salience (see, e.g., Kattenbeck, 2017; Winter, 2003). The interpretation also resembles the idea of an visibility index, which was, according to (Farr et al., 2012), introduced by Braaksma and Cook (1980). This index is based on the number of direct sight lines when moving towards a target (e.g., an intersection) and can be used as a direct measure of ease of wayfinding. Therefore, a wayfinder might need an instruction earlier in an occluded environment to make the wayfinding task easier as this allows the person to recognize the landmark of the upcoming turn earlier. Another explanation for the negative impact of the variables *LC_1* and *LC_2* could be that due to the perceived complexity of the environment which may be caused by the building density, wayfinders plan ahead in order to gain enough time to make the spatial decision and identify the object of interest among the possible plethora of landmarks.

6.1.2. Personal variables

[1]With respect to personal variables, our results suggest that participants older than 40 years of age tend to request route instructions later, a finding based on approx. 10% of all route segments. All of these participants have not only spent the largest fraction of their adulthood in Vienna but also considered their ability to find their way around in Vienna nearly all above average ($M = 71.1$, $min_{age>40} = 71$, $max_{age>40} = 100$). Therefore, it is reasonable to assume that the cognitive map(Tolman, 1948) or cognitive graphs (see Warren, 2019) of this group of people is well developed and, hence, had an impact on requesting a route instruction later as these mental representations develop over time based on experience (see, e.g., R. Kitchin, 1994): These persons are experienced wayfinders in this particular urban environment and, hence, they feel less pressure to reduce their uncertainty by requesting a route instruction early on. At the same time, our participants do not belong to an age group ($max_{age} = 59$) for which empirical evidence suggest that spatial abilities deteriorate (see, e.g., Head & Isom, 2010, who tested people with a mean age of 71 years). Our findings on age, however, are different to those reported in Giannopoulos et al. (2017), who found a main effect for both, age and the age group of people who are older than 27 years of age. Hence, further investigation of potential reasons for the difference found is one of the research questions opened up by the findings of the current study.

[1]A second finding with respect to personal variables relates to the participants' personality traits: People having a below average degree of openness (measured by the BFI-10 scale and according to norm data given in Rammstedt et al., 2012) request a route instruction earlier. Scholars tend to agree that human personality can be described along five dimensions (see John & Srivastava, 1999, for an overview on the history of these concepts), which are often referred to as *Big Five* (Goldberg, 1990): *extraversion*, *openness* to experience (also known as open-mindedness), *agreeableness*, *conscientiousness* and *emotional stability/neuroticism*. According to (Costa & McCrae, 2010), people who score high on trait *openness* "[. . .] enjoy novelty and variety [. . . and] have a high appreciation of beauty in art and nature" (Costa & McCrae, 2010, p. 243). The city of Vienna is, generally speaking, a city with a lot of historic buildings, with highly decorated facades. People having a low level of openness may, therefore, pay less attention to the beauty of this environment and ask for an instruction early on in order to have more time to focus on the wayfinding task itself.

6.1.3. Interactions between variables

[1]Drawing on common sense, a main effect of familiarity on timing seems plausible, i.e., we would have expected that people ask later for instructions when traveling on familiar routes (and vice versa). However, familiarity is only rendered significant as an interaction term: When walking through unfamiliar areas, persons request route instructions earlier on those segments which are longer than 120m. One potential explanation would be that the upcoming decision point is visible later on longer segments, for example due to a higher number of occluding objects on these segments. As a consequence, unfamiliar persons experience a higher degree of difficulty of wayfinding (Farr et al., 2012) and, hence, uncertainty due to their lack of a cognitive map/graph.

[1]When interpreting the meaning/influence of the interactions relating to spatial orientation, one needs to keep in mind how these values are calculated. We used the Ger-

man language self-report scale on spatial strategies developed by Münzer and Hölscher (2011). In analyzing this data, we follow the advice given in Kattenbeck and Kreuzpointner (n.d.): They provide evidence for the fact that a bifactor model for the scale fits a representative sample ($N = 4037$) of the German population better than the three-factor correlational model (involving the subfactors egocentric/global orientation (EGO), allocentric orientation and cardinal direction strategies) suggested by Münzer, Fehringer, and Kühl (2016). Kattenbeck and Kreuzpointner extract Sense of Direction (SOD) as a general factor from the data and provide evidence that the three subfactors remain significant. In their bifactor model, EGO can be interpreted as a person's preference for egocentric orientation. The obtained factor scores are standardized, i.e., zero represents an average self-report value. It is important to note, that in our sample all participants score above average (positive sign) on all four (sub-)factors.

[1]Our results suggest that there is a subgroup of people among the group of people who prefer egocentric orientation more than average: People scoring below three on the egocentric factor request route instructions on long segments (>120m) later. As the direction of this effect is counter-intuitive, further investigations in controlled settings are required to assess whether this effect holds across samples and what it actually means.

[1]Finally, the interaction terms suggest that the level of familiarity affects the timing of route instruction requests even for wayfinders with a high sense of direction: The higher the SOD of participants, the earlier they request the route instruction across conditions. However, for the unfamiliar condition, the route instruction is requested 20% earlier than in the familiar condition. This change aligns with the common sense expectation although it is dependent on a person's SOD. This effect, however, is contradicting the finding by Giannopoulos et al. (2017), who report a delaying effect by SOD on route instruction requests.

They argue the following: *"A possible interpretation of this result could be that the higher the spatial abilities, the higher the confidence of the wayfinder concerning the interpretation and mapping of instructions just before the decision point. Another interpretation could be that wayfinders with high spatial abilities wait longer in order to minimize the possible space where the given instructions can be mapped."*[Giannopoulos et al. (2017): Page 16:9]

The discrepancy of our results could be attributed to the difference in experimental setup. During our study, participants could request navigation instruction as often as they wanted. It could have been part of a display of higher spatial ability to strategically play the instruction sooner to already be aware of what the next action would be as in case of forgetting its content, the instruction could be requested later again.

[1]Aside from this possible explanation, this contradiction in modeling results raises, on the one hand, questions about ecological validity of controlled lab study results. On the other hand, it imposes questions about differences in self-report measurement of SOD, as Giannopoulos et al. (2017) base their results on the Santa Barbara Sense of Direction scale (Hegarty et al., 2002).

6.2. Model 2

6.2.1. Route variables

The GEE model in Table 6 contains two route variables.

The first one (*distance_of_landmark_visibility*) describes the distance between last visited major point and the position at which the landmark that is referenced in the present navigation instruction can be seen for the first time (see Figure 14 for graphical illustration). The calculation of this variable is based on two-dimensional OSM building footprint data and considers occlusion stemming only from buildings. Consequently, we can deduce that the advanced visibility of the landmark is shorter with increasing value of *distance_of_landmark_visibility*. The higher this distance is, the later the landmark is visible and the model suggests that an increase of this value increases the probability that people would want to hear a navigation instruction a second time.

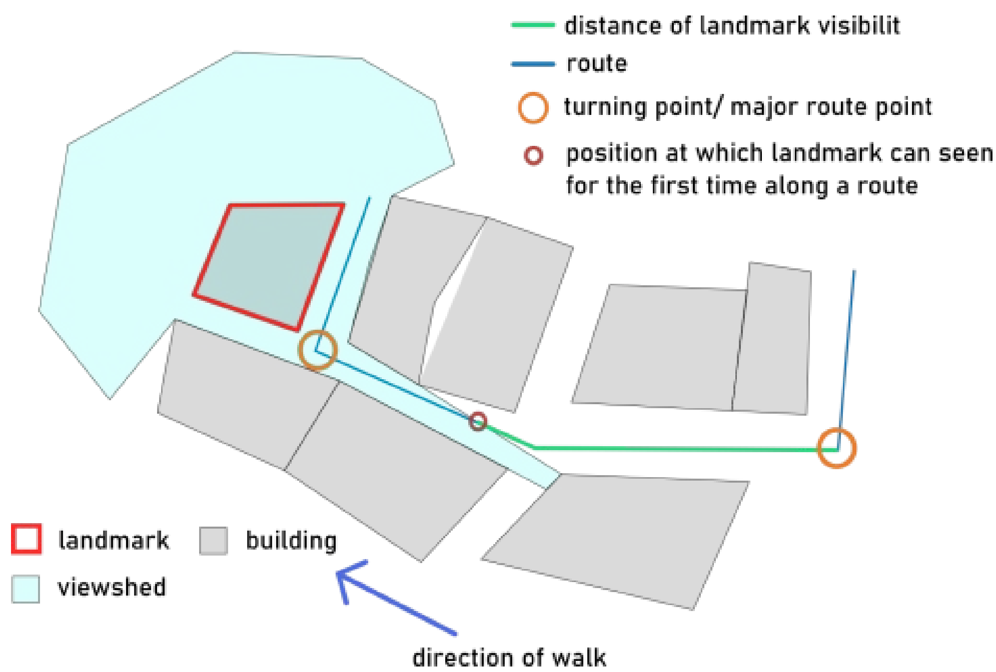

Figure 14: Explanation of variable *distance_of_landmark_visibility*. A viewshed (*blue polygon*) is calculated for the given landmark (indicated in *red*). The position at which the route (*blue line*) intersects the viewshed is the position at which the landmark is visible for the first time along the route. *distance_of_landmark_visibility* equals the distance between the previous major route point and this position (*green line*).

Based on empirical evidence, Kattenbeck (2017) suggests that the advanced visibility of a landmark is of significant importance for its salience and choosing salient objects has been an integral part of choosing suitable landmarks for reference in a route instruction (e.g. in). Winter (2003) suggests that seeing a landmark from the a further distance would decrease stress during wayfinding and be assuring to people that they are on the right track.

It is reasonable to assume that when people request a route instruction and cannot match the landmark immediately to an object, they would want to hear the instruction later again to either make sure that they did not miss a turn or because they later see the landmark and want to be certain that it corresponds to the object referenced in the instruction.

The dichotomous variable *last_instr_on_route* was introduced to the analysis to label the last united segments on all routes — in other words: the united segment between the last turning point and destination (see Figure 8 for graphical explanation of terminology). On these segments, the route instruction does not contain a description of a turn and refers only to the destination. The resulting model suggests that when people travel on the last united segment on a route, they tend to request the instruction only once. This can stem from two different sources: Either it is the fact that they are approaching the destination or the fact that the instruction does not contain an imperative to turn. One plausible explanation is that through the simplification of the instruction, it is easier to process and remember.

6.2.2. Environmental variables

The GEE model suggests that the presence of a health facility increases the probability of second request of for the route instruction (*amenity_health_present*). The variable summarizes the presence of medical practices, pharmacies, dentists and more. Due to the lack of reasonable explanation, the variable was further inspected and it was concluded that its significance to model stems for the most part from the occurrences of medical practices ($p < 0.001$) but maximum significance is yielded in the connection with the presence of pharmacies ($p < 0.0001$). The fact that, in Vienna, doctor's offices are usually not significantly salient arises the possibility that people themselves did not perceive it in the wayfinding situation.

It is plausible that this variable implies an effect that we have not measured. We checked for possible correlations with other environmental variables to inspect whether different environmental occurrences could hint at a possible explanation for this effect but no significant relation to other variables on the environmental level and other levels was found. Furthermore, the location of the routes for which this dichotomous variable equals 1, was inspected to look at possible explanations concerning the location of the routes in certain districts or areas of Vienna. At last, we observed whether the significance of this variable could be dependent on a mediating variable in the model by testing a uni-variable fit.

The lack of possible explanations arose the question whether including this variable in the first place was expedient and could be confounding for the model. To be sure to omit a possible confounding effect, we excluded the variable from the model and observed whether major changes would occur the parameters. While coefficient estimates all adjusted to the missing effect of the excluded variable, their signs and p-values stayed the same. Therefore, we conclude that the variable represents an environmental effect that we have not measured directly.

The model further suggests a decrease in probability of the occurrence of a second request in dependence of an increase of the point density of mobility infrastructure (see Table 4 for details on definition). The effect of this variable stems for the most part from POIs which are tagged to be for bicycle parking. They make up for about 77% of the total sum of the variable. Bicycle parking spots are most times located in open spaces such as parks and wide sidewalks. Therefore, the presence of multiple bicycle parking opportunities might imply fewer restriction of vision and therefore good visibility of the referenced landmark and the overview of the decision situation.

6.2.3. Behavioral data

In the GEE model, behavioral data describing the first request of a route instruction were used to predict whether the instruction would be requested a second time and the relative position of the first request on a united segment yielded significance ($rel\_click\_pos\_united\_seg$). This is calculated as the ratio between:

$$rel\_click\_pos\_united\_seg = \frac{distance \quad to \quad previous \quad major \quad route \quad point}{length \quad of \quad united \quad segment} \tag{15}$$

When this ratio increases, it is less likely that a second request will occur. Figure 15 illustrates this relation for better understanding. The effect of this ratio is an interaction between the increase of the counter and the decrease of the denominator. These variables have separately not yielded any significance in the classification model. We describe possible reasons for the effect of the variable by the means of examples:

Example 1 Alice makes a turn and approaches the upcoming intersection. She receives an instruction which references a landmark that is not located at the approached intersection. Therefore, she will have to continue straight ahead. The distance to the referenced turning point in the instruction is still about far ahead of her. She will want hear the instruction again to make sure that she is still on the right course and to remember where to turn.

Example 2 Alice makes a turn and listens to the route instruction right away. When she gets closer to the matching turning point, she wants to be sure that she is making the correct turn and wants to hear the instruction again.

Example 1 displays the effect of the increase of the denominator and *Example 2* the decrease of the counter. Based on this, it is very likely that the ratio in Formula 15 catches both of these effects.

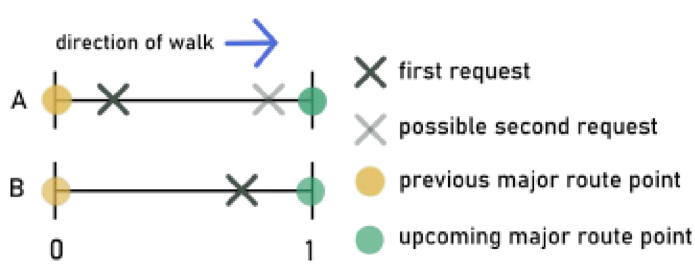

Figure 15: Explanation of effect of relative position of first request ($rel\_click\_pos\_united\_seg$). The distance to the last major route point is divided by the length of the united segment which is the distance between previous major route point and upcoming main route point. The values of $rel\_click\_pos\_united\_seg$ are therefore all in the range of [0,1]. In example **A**, the request is made earlier than in **B** and therefore, the probability that a second request will be made is lower in example **B** than in **B**.

6.2.4. Interaction terms

Our final GEE model yields significance for one interaction term. We first want to repeat the definition the variables involved for clarification: Let the time of the start of the experiment be t_0 and t_N the time at which the observed first request of the instruction is made, then $time\_passed\_since\_start = t_N - t_0(sec)$. BFI_n_high is a dichotomous variable and indicates whether a subject has a high score on the *neuroticism* subscale (greater than 4) of BFI-10 scale. Therefore, this term only effects the outcome variable for highly neurotic subjects otherwise it equals 0. It indicates that the probability of a second request of a navigation instruction decreases during a trial.

People with high BFI_n score are more prone to suffer from anxiety and stress (Costa & McCrae, 2010). It is therefore reasonable to suggest that these people feel stressed during the experiment. The stress might decrease in time for anxious people as they would get more comfortable and familiar with the experiment situation.

We do not know whether this is an effect that can be reduced to the experiment situation or whether people with a strong trait of neuroticism generally feel stressed when navigating. There is a questionnaire measuring spatial anxiety (Lawton, 1994) and it was reported that it correlates positively with making more errors during wayfinding (Hund & Minarik, 2006). It is unknown how and if neuroticism is related to spatial anxiety but it can be assumed that listening to a route instruction more often reduces uncertainty in wayfinding and therefore also the error rate in navigation.

6.3. Limitations

It is important to point out the limitations of our work. The first one concerns the generalizability of our study. The acquisition of participants might have led to a population sample that is not well representative.

[1]Our sample of participants includes only people who rate their sense of direction and spatial strategies above average (e.g., $min_{SOD} = 1.9$, $M_{SOD} = 4.8$). Hence, it remains unknown whether persons who are less well-oriented would have acted differently.

Secondly, the age distribution is far right-skewed; the lower quantile is $age_{0.25} = 23$ and upper $age_{0.75} = 26$. We had mostly participants within this range and very few older people.

Within the survival analysis, $N = 35$ segments on which people wanted to hear a navigation instruction before entering the segment or directly at the beginning had to be excluded as they could not be processed by AFT. This portion of segments needs to be analyzed separately in the future.

7. Conclusion

In this work, we analyzed data acquired in outdoor experiments to model preferred timing of instructions for pedestrians. We used similar experiment setup and methodology to predict when a person would want to hear a route instruction as Giannopoulos et al. (2017). Furthermore, we analyzed the preference of hearing a navigation instruction more than once. Rooted in previous findings on what variables might influence wayfinding behavior, we retrieved a range of personal, environmental and route-related features and yielded two models based on them: One predicting when a person would want to hear a route instruction and the other differentiating situations in which a person would want to hear a navigation instruction only once or more.

Based on our findings, we can conclude that variables of all considered groups have contributed the observed wayfinding behavior. Our results indicate familiarity with the environment and spatial abilities to be very important features. An interesting finding was that personality traits, namely *openness* and *neuroticism*, have also shown to be driving predictors of wayfinding behavior. Although their direct relation to wayfinding behavior and preferences is not known and further efforts have to be made to understand their effects, our results indicate the relevance of personalization of navigation systems.

Multiple environmental variables yielded to be significant and we interpreted them for the most part by tracing their effect back to advanced visibility of a landmark (*LC_1, LC_2, distance_of_landmark_visibility, amenity_mobility*). It is important to note that they are all derived from different data, none of them are true measures of advanced visibility and they also do not correlate significantly but can be interpreted as indicators for the importance of regarding advanced visibility in the prediction of preferred route instruction timing.

As the topic of timing of pedestrian route instruction was given little attention in the past, a range of questions were raised during the discussion of the results. A key question which remains unanswered concerns the motivation of requesting a navigation instruction at a certain point in time and how external information is influencing this decision. This still is in need to be studied. We propose two approaches to research this: The first one is to study the motivations by conducting experiments with think-aloud design. This could give insight to the cognitive processes which lead to requesting an instruction and support studying the role of spatial strategies in this context. The second one is to study the influence of environmental features in a highly controllable environment which would allow to alter landcovers, temporary objects on the street (e.g. cars, crowds) and vision occlusion to observe their direct impact on preferred timing.

The discussion has further raised questions concerning the comparison of results from different questionnaires measuring self-reported spatial abilities and strategies as we recognized differences in obtained models to the results of Giannopoulos et al. (2017) which could be further tracked back to the fact that our data was acquired during an outdoor study.

Besides the indication of importance of various factors, we can state, also based on the work of Giannopoulos et al. (2017), that the timing of navigation instructions is preferred differently depending on the user and environmental circumstances. This implies that there is a great potential in the adjustment of timing of instructions by pedestrian navigation systems to provide a comfortable wayfinding experience.

References

Agafonkin, V., & contributors, O. (n.d.). *Leaflet API.* https://leafletjs.com/reference-1.7.1.html.

Akaike, H. (1973). *Information theory and an extension of the maximum likelihood principle.* Budapest: Akadémiai Kiadó.

Akinwande, M. O., Dikko, H. G., Samson, A., et al. (2015). Variance inflation factor: as a condition for the inclusion of suppressor variable (s) in regression analysis. *Open Journal of Statistics*, *5*(07), 754.

Anastasopoulos, P. C., Islam, M. B., Perperidou, D., & Karlaftis, M. G. (2012). Hazard-based analysis of travel distance in urban environments: longitudinal data approach. *Journal of Urban Planning and Development*, *138*(1), 53–61.

Ballinger, G. A. (2004). Using generalized estimating equations for longitudinal data analysis. *Organizational Research Methods*, *7*(2), 127-150. Retrieved from https://doi.org/10.1177/1094428104263672 doi: 10.1177/1094428104263672

Barhorst-Cates, E. M., Rand, K. M., & Creem-Regehr, S. H. (2019). Navigating with peripheral field loss in a museum: learning impairments due to environmental complexity. *Cognitive Research: Principles and Implications*, *4*, 41. doi: 10.1186/s41235-019-0189-9

Bhat, C. R., & Pinjari, A. R. (2007). Duration modeling. In *Handbook of Transport Modelling: 2nd Edition* (pp. 105–131). Emerald Group Publishing Limited.

Bienk, S., Kattenbeck, M., Ludwig, B., Müller, M., & Ohm, C. (2013). I want to view it my way - interfaces to mobile maps should adapt to the user's orientation skills. In *Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia, MUM 2013.* doi: 10.1145/2541831.2541841

Boeing, G. (2017, 4). Osmnx: A python package to work with graph-theoretic openstreetmap street networks. *The Journal of Open Source Software*, *2*, 215. doi: 10.21105/joss.00215

Braaksma, J. P., & Cook, W. J. (1980). Human orientation in transportation terminals. *Transportation Engineering Journal of the American Society of Civil Engineers*, *106*(2), 189–203.

Brunyé, T. T., Gagnon, S. A., Gardony, A. L., Gopal, N., Holmes, A., Taylor, H. A., & Tenbrink, T. (2015). Where did it come from, where do you go? direction sources influence navigation decisions during spatial uncertainty. *Quarterly Journal of Experimental Psychology*, *68*, 585-607. doi: 10.1080/17470218.2014.963131

Brunyé, T. T., Gardony, A. L., Holmes, A., & Taylor, H. A. (2018). Spatial decision dynamics during wayfinding: intersections prompt the decision-making process. *Cognitive Research: Principles and Implications*, *3*. doi: 10.1186/s41235-018-0098-3

Brügger, A., Richter, K.-F., & Fabrikant, S. I. (2018). Which egocentric direction suffers from visual attention during aided wayfinding? In *Eye Tracking for Spatial Research, Proceedings of the 3rd International Workshop.* doi: https://doi.org/10.3929/ethz-b-000222472

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

Caduff, D., & Timpf, S. (2008). On the assessment of landmark salience for human navigation. *Cognitive Processing*, *9*(4), 249–267.

Cheraghi, S. A., Almadan, A., & Namboodiri, V. (2019, oct). CityGuide: A Seamless Indoor-Outdoor Wayfinding System for People With Vision Impairments. In *The 21st international acm sigaccess conference on computers and accessibility* (pp. 542–544). New York, NY, USA: ACM. doi: 10.1145/3308561.3354621

Core Team, R., et al. (2013). *R: A language and environment for statistical computing.* Vienna, Austria.

Costa, P. T., & McCrae, R. R. (2010). The NEO Inventories. In *Neo PI-R professional manual0* (pp. 223–256). American Psychological Association.

Datenschutzerklärung und Informed Consent zu Studien der Geoinformation. (2021). https://www.tuwien.at/index.php?eID=dms&s=4&path=Dokumente/Datenschutzerkl%C3%A4rungen%20Forschungsprojekte/Datenschutzerkl%C3%A4rung_Geoinformation.pdf. (Accessed: 2021-01-30)

Ding, D., Parmanto, B., Karimi, H. A., Roongpiboonsopit, D., Pramana, G., Conahan, T., & Kasemsuppakorn, P. (2007). Design considerations for a personalized wheelchair navigation system. In *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (p. 4790-4793). doi: 10.1109/IEMBS.2007.4353411

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

European Comission. (2012). *Mapping guide for a european urban atlas — copernicus.* Retrieved from https://land.copernicus.eu/user-corner/technical-library/urban-atlas-mapping-guide (last accessed November 30, 2020)

Fang, Z., Li, Q., & Shaw, S. L. (2015). What about people in pedestrian navigation? *Geo-Spatial Information Science*, *18*, 135-150. doi: 10.1080/10095020.2015.1126071

Farr, A. C., Kleinschmidt, T., Yarlagadda, P., & Mengersen, K. (2012). Wayfinding: A simple concept, a complex process. *Transport Reviews*, *32*, 715-743. doi: 10.1080/01441647.2012.712555

Geofabrik Download Server. (2018). https://download.geofabrik.de/. (Accessed: 2021-01-30)

Giannopoulos, I., Jonietz, D., Raubal, M., Sarlas, G., & Stähli, L. (2017). Timing of Pedestrian Navigation Instructions. In E. Clementini, M. Donnelly, M. Yuan, C. Kray, P. Fogliaroni, & A. Ballatore (Eds.), *13th International Conference on Spatial Information Theory (COSIT 2017)* (Vol. 86, pp. 16:1–16:13). Dagstuhl, Germany: Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik. doi: 10.4230/LIPIcs.COSIT.2017.16

Giannopoulos, I., Kiefer, P., & Raubal, M. (2015). Gaze nav: Gaze-based pedestrian navigation. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services* (p. 337-346). Association for Computing Machinery, Inc. doi: 10.1145/2785830.2785873

Giannopoulos, I., Kiefer, P., Raubal, M., Richter, K.-F., & Thrash, T. (2014). Wayfinding Decision Situations: A Conceptual Model and Evaluation. In *Proceedings of the 8th International Conference on Geographic Information Science (GIScience*

2014) (pp. 221–234). doi: 10.1007/978-3-319-11593-1_15

Golab, A. (2020a). *Familiarity.* https://www.geo.tuwien.ac.at/familiarity/index.html. (Accessed: 2021-01-30)

Golab, A. (2020b). *Route Planner.* https://www.geo.tuwien.ac.at/routeplanner/index.html. (Accessed: 2021-01-30)

Golab, A., Kattenbeck, M., Sarlas, G., & Giannopoulos, I. (n.d.). It's also about timing! When do pedestrians want to receive navigation instructions. *Spatial Cognition and Computation.* (in revision)

Goldberg, L. R. (1990). An alternative "description of personality": The Big-Five factor structure. *Journal of Personality and Social Psychology,*, *59*, 1216–1229.

Google Inc. (2020). *Google text-to-speech documentation.* Retrieved from https://cloud.google.com/text-to-speech/docs (accessed November 30, 2020)

Götze, J., & Boye, J. (2016). Learning landmark salience models from users' route instructions. *Journal of Location Based Services*, *10*, 47-63. doi: 10.1080/17489725.2016.1172739

Halekoh, U., Højsgaard, S., Yan, J., et al. (2006). The r package geepack for generalized estimating equations. *Journal of statistical software*, *15*(2), 1–11.

Hazzard, A., Benford, S., & Burnett, G. (2014). Walk this way: Musically guided walking experiences. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (p. 605-614). Association for Computing Machinery. doi: 10.1145/2556288.2557250

Head, D., & Isom, M. (2010, 5). Age effects on wayfinding and route learning skills. *Behavioural Brain Research*, *209*, 49-58. doi: 10.1016/j.bbr.2010.01.012

Hegarty, M., Richardson, A. E., Montello, D. R., Lovelace, K., & Subbiah, I. (2002). Development of a self-report measure of environmental spatial ability. *Intelligence*, *30*, 425-447.

Heidelberg Institute for Geoinformation Technology (HeiGIT). (2020). *openrouteservice.* https://openrouteservice.org/.

Hilbe, J. M., & Hardin, J. W. (2008). Generalized estimating equations for longitudinal panel analysis. *Handbook of longitudinal research: Design, measurement, and analysis*, *1*, 467–474.

Hirtle, S., Richter, K.-F., Srinivas, S., & Firth, R. (2010). This is the tricky part: When directions become difficult. *Journal of Spatial Information Science*(1), 53–73. doi: 10.5311/JOSIS.2010.1.5

Holland, S., Morse, D. R., & Gedenryd, H. (2002). AudioGPS: Spatial Audio Navigation with a Minimal Attention Interface. *Personal and Ubiquitous Computing*, *6*, 253–259. doi: 10.1007/s007790200025

Hosmer Jr, D. W., Lemeshow, S., & May, S. (2011). *Applied survival analysis: regression modeling of time-to-event data.* John Wiley & Sons.

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398). John Wiley & Sons.

Hund, A. M., & Minarik, J. L. (2006). Getting from here to there: Spatial anxiety, wayfinding strategies, direction type, and wayfinding efficiency. *Spatial Cognition & Computation*, *6*(3), 179-201. Retrieved from https://doi.org/10.1207/s15427633scc0603_1 doi: 10.1207/s15427633scc0603_1

Hölscher, C., Tenbrink, T., & Wiener, J. M. (2011). Would you follow your own route description? cognitive strategies in urban route planning. *Cognition*, *121*, 228-247. doi: 10.1016/j.cognition.2011.06.005

Ishikawa, T. (2019). Satellite navigation and geospatial awareness: Long-term effects of using navigation tools on wayfinding and spatial orientation. *Professional Geographer*, *71*. doi: 10.1080/00330124.2018.1479970

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In L. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (pp. 102–138). New York: Guilford Press.

Kalbfleisch, J. D., & Prentice, R. L. (2011). *The statistical analysis of failure time data* (Vol. 360). John Wiley & Sons.

Kattenbeck, M. (2017). How subdimensions of salience influence each other. comparing models based on empirical data. In *Proceedings of the 13th International Conference on Spatial Information Theory (COSIT 2017)* (Vol. 86, pp. 1–10). doi: 10.4230/LIPIcs.COSIT.2017.10

Kattenbeck, M., & Kreuzpointner, L. (n.d.). Sense of Direction and Spatial Strategies. A Bifactor Structure for the Spatial Strategies Questionnaire Fragebogen Räumliche Strategien. *PLoS One*. (in revision)

Kattenbeck, M., Nuhn, E., & Timpf, S. (2018). Is salience robust? A heterogeneity analysis of survey ratings. In *10th International Conference on Geographic Information Science (GIScience 2018)* (Vol. 114, p. 1-7). doi: 10.4230/LIPIcs.GIScience.2018.7

Kitchin, R. (1994). Spatial familiarity as a variable in cognitive mapping. *Swansea Geographer*, *31*, 42-52.

Kitchin, R. M. (1994). Cognitive maps: What are they and why study them? *Journal of Environmental Psychology*, *14*(1), 1 - 19. Retrieved from http://www.sciencedirect.com/science/article/pii/S027249440580194X doi: https://doi.org/10.1016/S0272-4944(05)80194-X

Kitchin, R. M., Blades, M., & Golledge, R. G. (1997). Relations between psychology and geography. *Environment and Behavior*, *29*(4), 554-573. Retrieved from https://doi.org/10.1177/001391659702900406 doi: 10.1177/001391659702900406

Klippel, A., Richter, K. F., & Hansen, S. (2009). Cognitively ergonomic route directions. *Handbook of Research on Geoinformatics*, 230–238. doi: 10.4018/978-1-59140-995-3.ch029

Klippel, A., Tappe, H., & Habel, C. (2002). Pictorial representations of routes: Chunking route segments during comprehension. In *International Conference on Spatial Cognition* (pp. 11–33).

Kozlowski, L. T., & Bryant, K. J. (1977). Sense of direction, spatial orientation, and cognitive maps. *Journal of Experimental Psychology: human perception and performance*, *3*(4), 590.

Krukar, J., Anacta, V. J., & Schwering, A. (2020). The effect of orientation instructions on the recall and reuse of route and survey elements in wayfinding descriptions. *Journal of Environmental Psychology*, *68*, 101407. doi: 10.1016/j.jenvp.2020.101407

Lander, C., Herbig, N., Löchtefeld, M., Wiehr, F., & Krüger, A. (2017). Inferring landmarks for pedestrian navigation from mobile eye-tracking data and google street view. *Conference on Human Factors in Computing Systems - Proceedings, Part F1276*, 2721-2729. doi: 10.1145/3027063.3053201

Lawton, C. A. (1994). Gender differences in way-finding strategies: Relationship to spatial ability and spatial anxiety. *Sex Roles*, *30*, 765-779. doi: 10.1007/BF01544230

Lazem, S. Y., & Sheta, W. M. (2005). Automatic Landmark Identification in Large Virtual Environment: A Spatial Data Mining Approach. In *Proceedings of the Ninth International Conference on Information Visualisation (IV'05)* (p. 752-757). IEEE Computer Society.

Liang, K.-Y., & Zeger, S. L. (1986, 04). Longitudinal data analysis using generalized linear models. *Biometrika*, *73*(1), 13-22. Retrieved from https://doi.org/10.1093/biomet/73.1.13 doi: 10.1093/biomet/73.1.13

LimeSurvey. (2020). https://limesurvey.geo.tuwien.ac.at/. (Accessed: 2021-01-30)

Liu, X. (2014). Survival models on unobserved heterogeneity and their applications in analyzing large-scale survey data. *Journal of biometrics & biostatistics*, *5*.

Liu, X. (2015). *Methods and applications of longitudinal data analysis.* Elsevier.

Lovelace, K. L., Hegarty, M., & Montello, D. R. (1999). Elements of good route directions in familiar and unfamiliar environments. *Spatial Information Theory: Cognitive and Computational Foundations of Geographic Information Science*, 65-82.

May, A. J., Ross, T., Bayer, S. H., & Tarkiainen, M. J. (2003). Pedestrian navigation aids: information requirements and design implications. *Personal and Ubiquitous Computing*, *7*, 331-338.

Michon, P.-E., & Denis, M. (2001). When and why are visual landmarks used in giving directions? In *International Conference on Spatial Information Theory (COSIT 2001)* (pp. 292–305).

Montello, D. R. (2005). Navigation. In *The Cambridge Hanbook of Visuospatial Thinking* (p. 257-294). Cambridge University Press.

Münzer, S., Fehringer, B. C., & Kühl, T. (2016). Validation of a 3-factor structure of spatial strategies and relations to possession and usage of navigational aids. *Journal of Environmental Psychology*, *47*. doi: 10.1016/j.jenvp.2016.04.017

Münzer, S., & Hölscher, C. (2011). Entwicklung und Validierung eines Fragebogens zu räumlichen Strategien. *Diagnostica*, *57*(3), 111–125.

Münzer, S., & Hölscher, C. (2011). Entwicklung und Validierung eines Fragebogens zu räumlichen Strategien. , *57*, 111-125.

Nelder, J. A., & Wedderburn, R. W. M. (1992). Generalized linear models. In S. Kotz & N. L. Johnson (Eds.), *Breakthroughs in statistics: Methodology and distribution* (pp. 547–563). New York, NY: Springer New York. Retrieved from https://doi.org/10.1007/978-1-4612-4380-9_39 doi: 10.1007/978-1-4612-4380-9_39

Nothegger, C., Winter, S., & Raubal, M. (2004). Selection of salient features for route directions. *Spatial Cognition & Computation*, *4*, 113-136.

Nuhn, E., & Timpf, S. (2017). A multidimensional model for selecting personalised landmarks. *Journal of Location Based Services*, *11*, 153-180. doi: 10.1080/17489725.2017.1401129

Nuhn, E., & Timpf, S. (2020). How to Model (Personalised) Landmarks ? In

J. Šķilters, N. Newcombe, & D. Uttal (Eds.), *Spatial Cognition XII. Spatial Cognition 2020* (p. 33-49). Springer International Publishing. doi: 10.1007/978-3-030-57983-8

OpenStreetMap contributors. (2017). *Planet dump retrieved from https://planet.osm.org* . https://www.openstreetmap.org.

Pan, W. (2001). Akaike's information criterion in generalized estimating equations. *Biometrics*, *57*(1), 120-125. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0006-341X.2001.00120.x doi: https://doi.org/10.1111/j.0006-341X.2001.00120.x

Pekár, S., & Brabec, M. (2018). Generalized estimating equations: A pragmatic and flexible approach to the marginal glm modelling of correlated data in the behavioural sciences. *Ethology*, *124*(2), 86-93. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/eth.12713 doi: https://doi.org/10.1111/eth.12713

POI display. (2013). https://wiki.openstreetmap.org/wiki/POI_display. (Accessed: 2021-01-30)

Quesnot, T., & Roche, S. (2015). Quantifying the Significance of Semantic Landmarks in Familiar and Unfamiliar Environments. In S. I. Fabrikant, M. Raubal, M. Bertolotto, C. Davies, S. Freundschuh, & S. Bell (Eds.), *Proceedings of the international conference on spatial information theory* (Vol. 9368, p. 468-489). Springer International Publishing.

Rammstedt, B., Kemper, C. J., Klein, M. C., Beierlein, C., & Kovaleva, A. (2012). Eine kurze skala zur messung der fünf dimensionen der persönlichkeit: Big-five-inventory-10 (bfi-10).

Raubal, M., & Winter, S. (2002). Enriching wayfinding instructions with local landmarks. In M. Egenhofer & D. Mark (Eds.), *International conference on geographic information science* (p. 243-259). Springer.

Rehrl, K., Häusler, E., Leitinger, S., & Bell, D. (2014). Pedestrian navigation with augmented reality, voice and digital map: final results from an in situ field study assessing performance and user experience. *Journal of Location Based Services*, *8*(2), 75–96.

Richter, K.-F., & Klippel, A. (2005). A Model for Context-Specific Route Directions. In C. Freksa, M. Knauff, B. Krieg-Brückner, B. Nebel, & T. Barkowsky (Eds.), *Spatial Cognition IV. Reasoning, Action, Interaction. Spatial Cognition 2004* (p. 58-78). doi: 10.1007/978-3-540-32255-9_4

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

Ross, T., May, A., & Thompson, S. (2004). The Use of Landmarks in Pedestrian Navigation Instructions and the Effects of Context. In *International Conference on Mobile Human-Computer Interaction Mobile HCI 2004* (p. 300-304). doi: 10.1007/978-3-540-28637-0_26

Rousell, A., & Zipf, A. (2017). Towards a landmark-based pedestrian navigation service using OSM data. *ISPRS International Journal of Geo-Information*, *6*(3). doi: 10.3390/ijgi6030064

Sarjakoski, T., Kettunen, P., Halkosaari, H.-M., Laakso, M., Rönneberg, M., Stigmar, H., & Sarjakoski, T. (2013). Landmarks and a Hiking Ontology to Support Wayfinding in a National Park During Different Seasons. In M. Raubal, D. M. Mark, & A. U. Frank (Eds.), *Cognitive and Linguistic Aspects of Geographic Space. New Perspectives on Geographic Information Research.* Heidelberg et al.: Springer.

Sarlas, G., & Axhausen, K. W. (2018). Commuting distance and individual accessibility. *Arbeitsberichte Verkehrs-und Raumplanung, IVT, ETH Zurich*, *1376*.

Schmidt, A., Beigl, M., & Gellersen, H.-W. (1999). There is more to context than location. *Computers & Graphics*, *23*, 901.

Schwering, A., Krukar, J., Li, R., Anacta, V. J., & Fuest, S. (2017). Wayfinding through orientation. *Spatial Cognition and Computation*, *17*, 273-303. doi: 10.1080/13875868.2017.1322597

Shaffer, M. L., & Hiriote, S. (2009). Analysis of time-to-event and duration outcomes in neonatal clinical trials with twin births. *Contemporary Clinical Trials*, *30*(2), 150 - 154. Retrieved from `http://www.sciencedirect.com/science/article/pii/S1551714408001481` doi: https://doi.org/10.1016/j.cct.2008.11.001

Stern, E., & Portugali, J. (1999a). Environmental cognition and decision making in urban navigation. *Wayfinding behavior: Cognitive mapping and other spatial processes*, 99–119.

Stern, E., & Portugali, J. (1999b). Environmental cognition and decision making in urban navigation. *Wayfinding behavior: Cognitive mapping and other spatial processes*, 99-119.

Stähli, L., Giannopoulos, I., & Raubal, M. (2020). Evaluation of pedestrian navigation in smart cities. *Environment and Planning B: Urban Analytics and City Science*, 1-18. doi: 10.1177/2399808320949538

Therneau, T. (2014). A package for survival analysis in S. R package version 2.37-4.

Tolman, E. C. (1948). Cognitive Maps in Rats and Men. *Psychological Review*, *55*(4), 189–208.

Tom, A., & Denis, M. (2004). Language and spatial cognition: comparing the roles of landmarks and street names in route instructions. *Applied Cognitive Psychology*, *18*(9), 1213-1230. doi: https://doi.org/10.1002/acp.1045

Visual Paradigm. (2021). `https://online.visual-paradigm.com/de/diagrams/features/erd-tool/`. (Accessed: 2021-01-31)

Völkel, T., & Weber, G. (2008). Routecheckr: personalized multicriteria routing for mobility impaired pedestrians. In *Proceedings of the 10th international ACM SIGACCESS conference on Computers and accessibility* (pp. 185–192).

Waldorf, B. (2003). Spatial patterns and processes in a longitudinal framework. *International Regional Science Review*, *26*(3), 269–288.

Walther-Franks, B., & Malaka, R. (2008). Evaluation of an augmented photograph-based pedestrian navigation system. In A. Butz, B. Fisher, A. Krüger, P. Olivier, & M. Christie (Eds.), *Smart Graphics* (pp. 94–105). Berlin, Heidelberg: Springer Berlin Heidelberg.

Wang, J., & Ishikawa, T. (2018). A system of automatic generation of landmark-based pedestrian navigation instructions and its effectiveness for wayfinding. In *German Conference on Spatial Cognition* (pp. 326–340).

Wang, M. (n.d.). Generalized estimating equations in longitudinal data analysis: A review and recent developments. *Advances in Statistics*, *2014*.

Warren, W. H. (2019, 2). Non-euclidean navigation. *The Journal of Experimental Biology*, *222*, 1-10. doi: 10.1242/jeb.187971

Winter, S. (2003). Route adaptive selection of salient features. In *International conference on spatial information theory* (pp. 349–361).

Zeger, S. L., & Liang, K.-Y. (1986). Longitudinal data analysis for discrete and continuous outcomes. *Biometrics*, *42*(1), 121–130. Retrieved from http://www.jstor.org/stable/2531248

Zimmer, H. D., Münzer, S., & Baus, J. (2010). From resource-adaptive navigation assistance to augmented cognition. In *Resource-Adaptive Cognitive Processes* (pp. 35–53). Springer.

A. Online Questionnaire

Participants were acquired through announcements during lectures, over postings on social media, with the help of the student body of the Department of Geodesy and Geoinformation at TU Wien and by spreading the word through colleagues and the social connections. A flyer with important facts about the experiment was used to convey what the experiment is for and encourage participation (see Figure 16).

Figure 16: Flyer which was spread electronically and physically to acquire participants.

The duration of the experiment was estimated to be 1,5h (30 min online questionnaire, 1h for 2 outdoor trials). To make participation even more appealing, it was advertised that two out of all participants would win a voucher worth €100,-.

The first step of participation encompassed the registration to the experiment and answering multiple questionnaires. This was done using the service *LimeSurvey* (2020).

A.1. Registration and questionnaires

The *LimeSurvey* survey was structures in the following way:

- Information on Experiment
- Consent to data acquisition during outdoor experiment using eye-tracking device, IMU motion sensor, GPS-antenna and sensors in smartphone and data processing
- Consent to processing of demographic data
- Data protection declaration and informed consent by Research Division Geoinformation, TU Wien (*Datenschutzerklärung und Informed Consent zu Studien der Geoinformation*, 2021)
- Specification of e-mail address and consent to it being used to contact participant for experiment-related matters
- Consent to participation in lottery
- Questionnaire *Fragebogen zum Orientierungssinn (FRS)* by Münzer and Hölscher (2011)
- Questions about demographic data
  - Gender (possible anwers, single choice: *female/male*)
  - Age
  - *What navigational aid do you use while navigating as a pedestrian?* possible answers (multiple choice):
    * (street) signs
    * navigation system on mobile phone
    * ask other pedestrians
    * map
    * other (free input)
  - *How well do you find your way around in Vienna?* (numerical answer between 0 and 100, 0 = *I do not find my way around Vienna at all* and 100 = *I find my way anyway in Vienna*)
- *Big-Five-Inventory 10* (Rammstedt et al., 2012)

A.2. Disclosure of familiarity-related information

The collection of information about familiar places in Vienna was important to design routes on which people would be truly familiar with the environment. For this, two websites were programmed using `Java Script` for programming the user-interface, `PostgreSQL 12` as a database and `PHP` server. Further, the following services were utilized:

- *Leaflet* by (Agafonkin & contributors, n.d.) for map display and drawing tools
- *Openrouteservice* by (Heidelberg Institute for Geoinformation Technology (HeiGIT), 2020) was used to retrieve distances of shortest path between markers

Optimization of UI The design of these websites was carefully conducted. On the one hand-side, it was important to provide a simple and understandable user interface and, on the other hand-side, to obtain the desired results for determining familiar and unfamiliar routes. Additionally, it was crucial that the entire online registration would only take 30min and therefore, the disclosure of information on familiar places should only take 15min in total.

With these goals in mind, pretesting was conducted as an iterative process:

1. **Step 1**: Multiple people (~5) were presented with a printed map and a pen and were asked *Can you please tell me where you know your way around Vienna by the means of this map?*. The goal of this was to observe how people would react to this instruction and how they would prefer to indicate areas or places they know. Only one person pointed at streets and routes he/she knows in Vienna. The others were circling districts and large and small areas. Based on this, I concluded that the webpage will have to allow to highlight familiar areas using a polygons.

2. **Step 2**: After a first draft was implemented, the interface was tested by asking people (~4) to follow singular instructions. They key issue in this step was to phrase the instruction to highlight a familiar area using a polygon from the tool bar in the interface. The key findings were that the word *polygon* is not understood by most and that the functionalities of the tool bar are best understood when using the originally provided icons by *Leaflet*.

3. **Step 3**: Finally, both websites were fully implemented and presented to five more people. In this step, I asked people to think aloud to observe how instructions were understood and what features of the user-interface still were difficult to use while also keeping an eye on much time the tasks take. This helped in further simplification and making the user-interface more understandable. During this process, instructions were vastly shortened to save time and made understandable in fewer sentences. It became evident that people would need to see examples of how such a highlighted areas and placed markers within them should looked like. This was a very crucial point because before, I did not want to include an example due to fearing to induce a bias in how areas would be circled and what places would be marked. Though, it was necessary to convey certain key attributes about the polygon and the placement of the markers (the polygon should highlight big areas and markers should be placed geographically evenly spread within it). I chose to display an unrealistic example in the city of Salzburg with a marker placed in the city center with the place description *IKEA*. Introducing examples helped further in the simplification and shortening of instructions. They were important to yield desired outcomes. Moreover, I recognized that people need to know how many polygons to draw and markers to place as during pretesting, I was asked this frequently and no knowing this made them feel insecure on how long to continue.

It is important to note here that people who were part of this pretesting were not further allowed to participate in the experiment.

Additionally to the findings due to pretesting, we added in the instructions that we would prefer if people would avoid outlining the city center. This choice was made because we later assigned each *familiar* route as *unfamiliar* to others. In the pretesting phase, we observed that many would focus on outlining the city center which would complicate the route matching.

Graphical UI During the registration process, participants were assigned a *participant-ID* and after filling out the questionnaires, they were forwarded to https://www.geo.tuwien.ac.at/familiarity/index.html (Golab, 2020a) where they were automatically logged-in with the same participant-ID.

The graphical UI looked the following way:

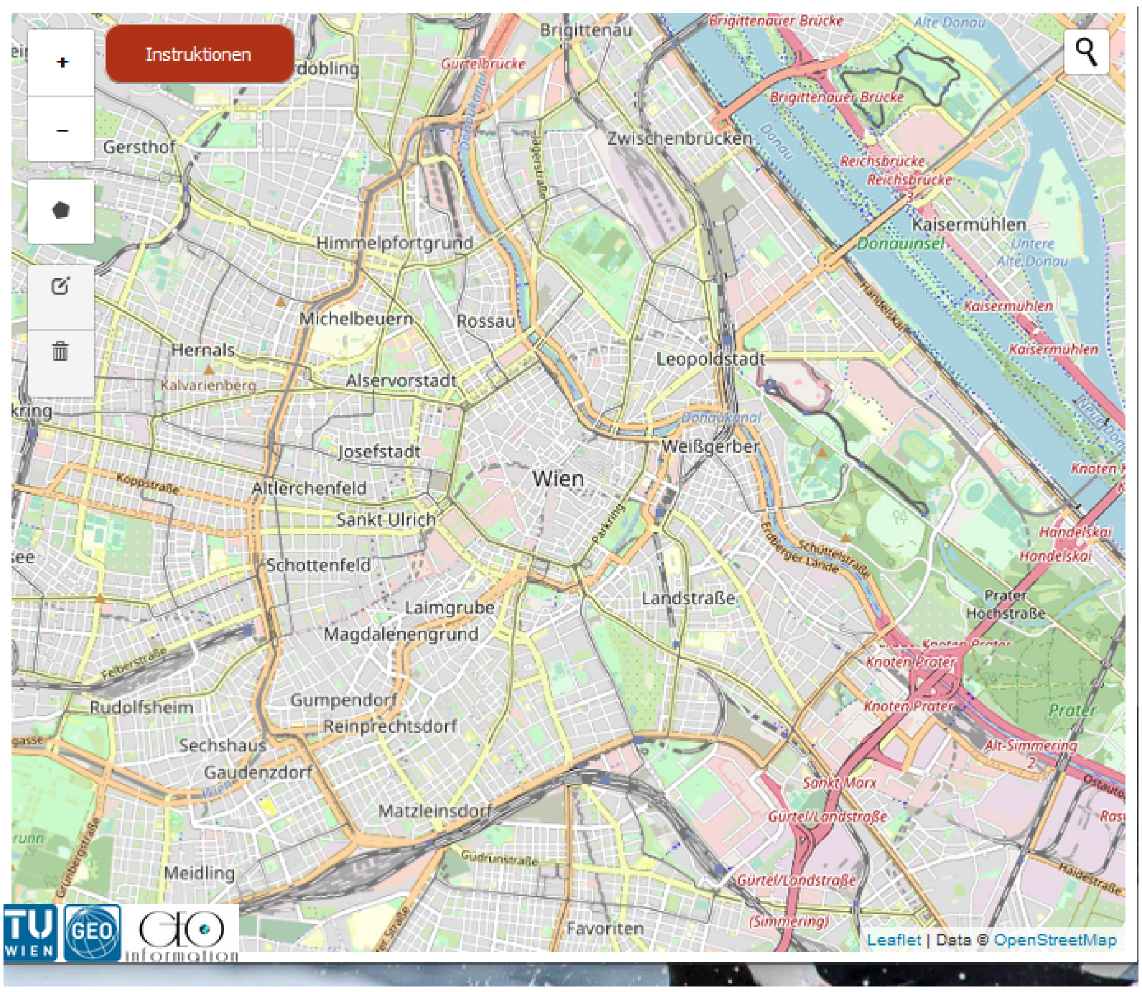

Figure 17: UI. The displayed map was centered on the city of Vienna. Drawing tools were located on the top left and the user could any time take a look at the instructions again by clicking the button *Instruktionen*.

They were then presented these instructions[1]:

[1] All instructions are here displayed in German language. If a translation to English is needed, I will gladly help.

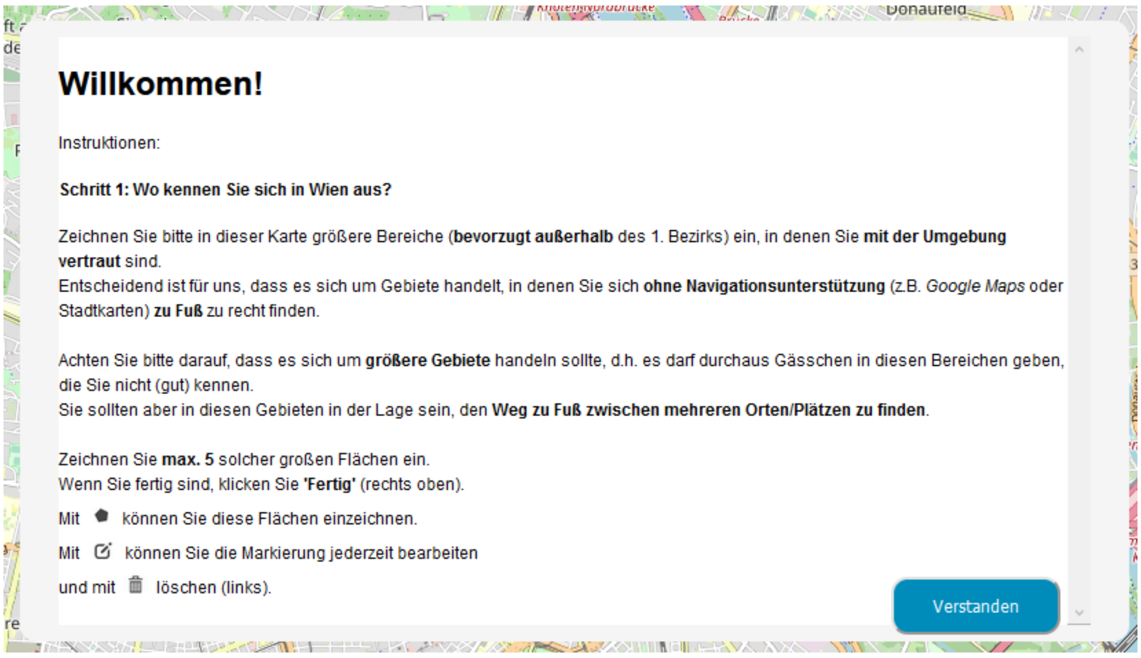

Figure 18: These instructions explain how to highlight familiar areas and how to use the tools in the UI to do this.

After clicking button *Verstanden* which is translated to *understood* in English, an example of what the drawn area should look like is displayed:

Figure 19: Example highlighted area in instructions.

After highlighting all familiar areas, participants proceeded to place markers on familiar places and naming them, following these instructions:

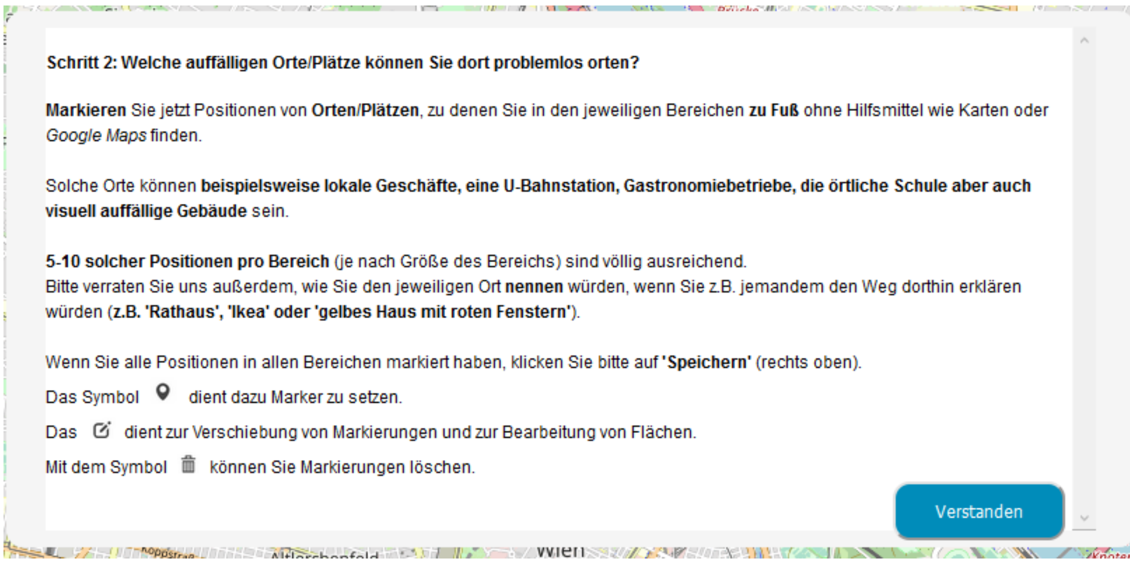

Figure 20: The placement of markers is explained by the means of an example.

An illustration of how the markers should be geographically evenly spread in a polygon was displayed to the user:

Figure 21: Example placement of markers.

After participants were finished, the geographic data was forwarded to be saved to the database.

Route generation The second website was designed to randomly decide a starting and end point for the route, and to draw a route between them (https://www.geo.tuwien.ac.at/routeplanner/index.html, Golab, 2020b). The random assignment was done by considering marker pairings which were within the distance of the threshold [900,1300]m and choosing one of them randomly. Then, the algorithm decided which one of these would be the starting point and the end point of the route, again at random. A URL to the website was send to participants, so they could draw a route they would choose between the familiar places.

They followed these instructions:

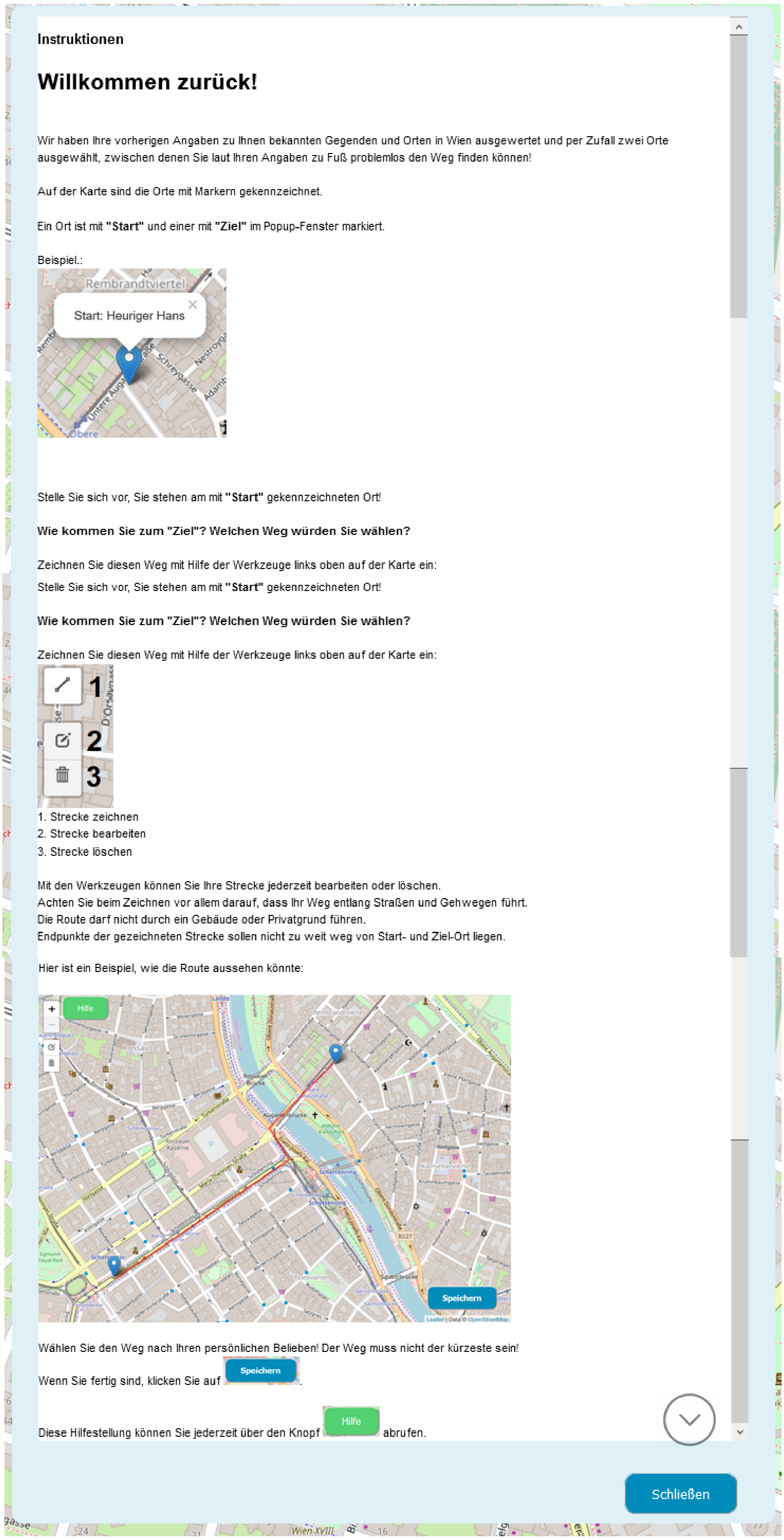

Figure 22: These instructions direct how to draw a route that between the marker highlighted as starting point and end point.

Database structure For each participant, all polygons, markers and travel distances between markers within the polygons were saved. The distances between the markers were retrieved using *Openrouteservice* by Heidelberg Institute for Geoinformation Technology (HeiGIT) (2020).

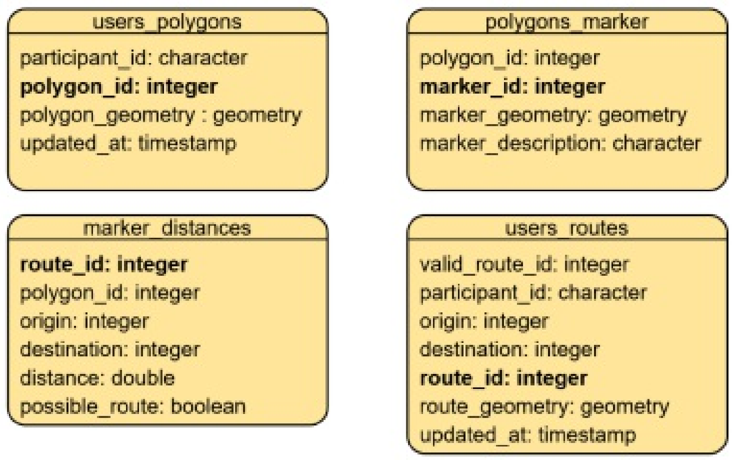

Figure 23: Database scheme in which all information on familiar areas, places and routes is saved. (illustration created using *Visual Paradigm* (2021))

B. Landmark algorithm

The landmark algorithm was designed after Rousell and Zipf (2017). A step-wise procedure was implemented to yield landmarks for the routes which were drawn by participants:

- Projecting the route to the street network
- Determination of turning points
- Obtaining a suitable landmark

Projecting the route to the street network *Starting point*: The participant has drawn a route which is saved in the database (*users_routes*, Figure 23). This route was drawn precise enough to convey the information how the route would run but we have no information about turning points. In this step, we aim to obtain a linestring that consists only of major route points. We specifically want to obtain turning points have the same coordinates as an OSM junction node to conduct our calculations with high accuracy.
The projection is here rather a simple one but is sufficient enough to obtain the turning points: For each participant, we take the route from the database, we retrieve the drawn points from the linestring and project each point to the street network. We do not do this by simply finding the nearest node but by finding the nearest street segment first and then projecting the point to the nearest end point of this street segment. These *projected* points are then connected by calculating the shortest path between them. This procedure yields our *projected* route.

Determination of turning points The algorithm explained above has further created a csv-file and visualizations of the projected route. We make a copy of the csv-file and add a row called *turn*. Now we inspect the visualizations and classify by hand which points along the route are turning points. Another algorithm will visualize our manual work to make sure we did not miss a turning point during this procedure.

Figure 24: The *blue* line is drawn by the participant, *red* line is connecting major route points (*red* dots) and the *line* is the projected route. (*background*: *Leaflet*)

Obtaining a suitable landmark Finally, the information of major route points with coordinates and turn information is saved to a *csv*-file which is used to determine a landmark for each turning point. During the landmark algorithm, we take a turning point and its previous major route points to determine a suitable landmark using the algorithm by (Rousell & Zipf, 2017). The final product is a csv-file containing all potential landmarks sorted after suitability value for each turning points. It further holds all calculated values which allows us to check whether f.e. the value for visibility was wrongly determined due to wrong projection of a point to building edge. This csv-file was very helpful for the visits of the route in-situ.

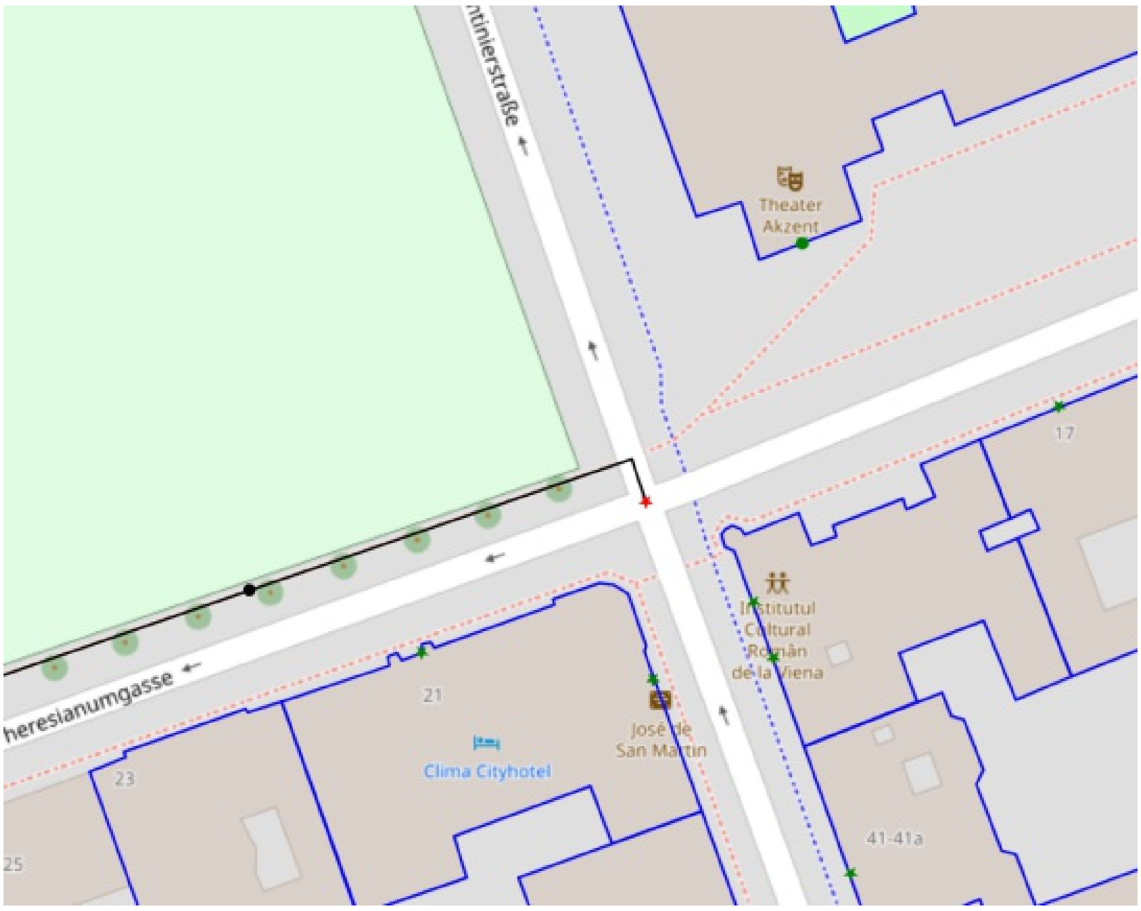

Figure 25: Result of landmark algorithm. The *red* star indicates the position of the decision point. *Green stars* are potential landmarks, while the *green* circle is the chosen landmark. The *black* circle is the position 50m before arriving at the decision point (*background*: *Leaflet*)

.

C. Details on experimental setup

Pre-experiments The design of the outdoor experiment was pre-tested using two participants. This was important to test how long a trial would take and if instructions for the experiment would be understood by the participants. During the first experiment, the fact that navigation instructions were design exclusively for turning points was not explained. It was observed that this resulted in confusion and miss-understanding during the experiment. After introducing this to the experiment protocol, the second pre-test was successful.

Procedures before setup Before the participant arrived at the location of the experiment, devices were prepared for its usage:

- xSens MTi-300 IMU device was calibrated.
- An internet connection was set up on the laptop.
- GPS-antenna (PPM 10-xx38) was connected to the laptop.
- As soon as the GPS-antenna received a signal, the laptop time was synchronized with GPS time.
- The time of the IMU was synchronized to laptop time. By doing this, GPS-Antenna, IMU and laptop would all use the same time.

Setup Participants were wearing an eye-tracking device (PupilLabs Invisible). It was calibrated for each participant using an object in 15m distance. This choice was made based on previously tested depths of calibrations and the assumption that this would be the medium distance of where the participants would be looking during the experiment. The eye-tracking device was connected to a mobile phone. On the head, participants had a cap with the xSens MTi-300 IMU device that was attached to the cap using duck tape. It was important that the cap would fit properly and not slide on the head as I wanted to measure head movements. The IMU device was connected to the laptop, so was the GPS receiver (PPM 10-xx38). The laptop was located in the transparent rucksack which participants were wearing on their back. The phone which was connected to the eye-tracking device was also located there. Moreover, I attempted to log measurements of phone sensors (gyroscope, magnetometer, etc.). Therefore, participants put a phone in their pocket which was saving all measurements of phone internal sensors during the experiment. To hear navigation instructions, participants wore Bluetooth earpods which were connected to the phone of the experiment conductor. This phone not only played navigation instructions and logged the time of request but further was used to save the exact time of experiment start and end. Lastly, participants were equipped with a clicking device that lit up a red light which was located in the back of the rucksack. Participants initiated a request for a navigation instruction by using the clicking device.

Synchronization For each of the devices used during the experiment, the time was different. I had to therefore determine the time differences before processing steps could be applied.

Before the start of the experiment, a procedure was conducted which allowed to synchronize the times. It was essential to synchronize the times of the laptop to which IMU device and GPS-antenna were connected, the eye-tracking measurements and both phones. This procedure was the following:

1. Eye-Tracking measurement was started.
2. On the experiment conductor's phone an application was opened which allowed to display the current time of the system.
3. The participant was asked to hold the phone, look at it and press the button *GET TIMESTAMP* which displayed a time stamp of the system time at the moment the button was clicked.
4. The similar was done with the phone recording internal sensor measurements.
5. On the laptop, a `Java` program was opened and the person had to look at the screen while the a timestamp of the current system time was printed.

The time stamps of different system times were recorded by the eye-tracking device and through referencing each time to a frame in the eye-tracking video the time synchronization was possible.

D. Data Preprocessing

D.1. Segmentation

The segmentation process had two key challenges:

- Choosing appropriate OSM junctions points
- Partitioning the route in a correct way

The problem statement is the following: A GPS track is obtained during a trial and we want to be able to reference behavioral data to a segment. As a segment, we define a part of a route between two intersections or between the start point or destination and an intersection.

Choosing appropriate junction points The challenge here was twofold: On the one hand-side, it is unknown which junctions are perceived by a participant as possible turning-points. On the other hand-side, it is not expedient to use all available junctions for segmentation, for example, in the following case:

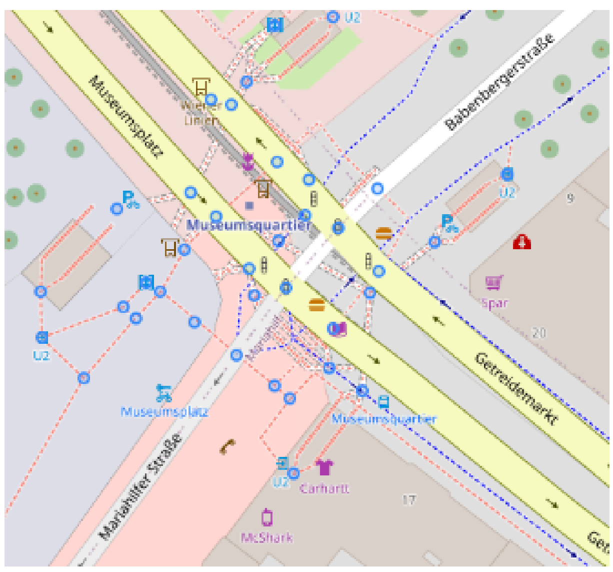

Figure 26: The *blue* circles indicate positions of junction points in OSM (*background*: OpenStreetMap contributors (2017))

If a route would be passing this intersection, using all the junctions for segmentation here would yield many small segments which would not be useful for further processing. Another possibility would be to use only intersections for cars but this approach would assume that participants do not perceive a junction with a pathway that leads, f.e., into a park as a possibility to turn.

I faced this issue by designing the following procedure:

1. A buffer of 30m radius is drawn around the route.
2. *Road*[2] intersections are retrieved within this buffer.
3. Further, *path*[3] intersections are retrieved separately.
4. Buffers with the radius of 50m are drawn around all *road* intersections.

[2]intersections for both cars and pedestrians
[3]intersections for pedestrians

5. All *path* intersections that lie within these buffers are deleted.

6. The remaining *path* intersections and *road* intersections are taken into further consideration.

This a-priori selection of intersections was displayed on a map with the route and examined. Manually, intersections that were falsely excluded and falsely included were noted. Such decisions were made following this criteria:

- A *path* intersection is because it is located near a *road* intersection. However, this intersection has been falsely excluded if it is connected to a pathway which is not parallel to a road and is therefore a seperate possibility to turn for pedestrians.

- The route is parallel to a double lane. At an intersection, two *road* intersections are located at the same level. The further one is excluded because keeping both for the segmentation procedure would yield again very small unnecessary segments.

Figure 27: The route (*blue* line) here is parallel to the double lane. At the intersection, two road intersection exist. We only choose one of these (*black* circle) and exclude the *grey* circle (*background*: OpenStreetMap contributors (2017)).

- Because OSM data is two-dimensional, junctions of underground paths appear as they would be on the surface. Such junctions have to identified and excluded.

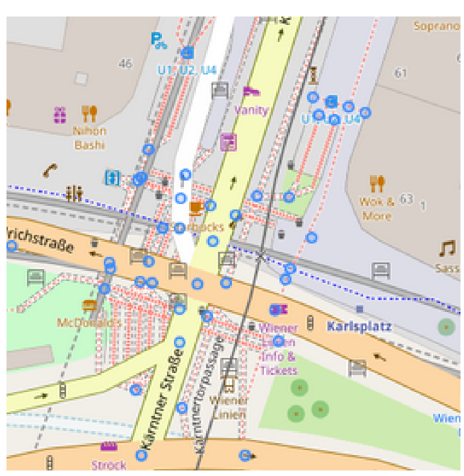

Figure 28: An underground metro station is located here and all intersections of path ways are displayed as if there were on the surface (*background*: OpenStreetMap contributors (2017)).

Partitioning the route After appropriate intersections were determined, it had to be decided how the route would be "sliced". The ideal situation is illustrated in the following Figure:

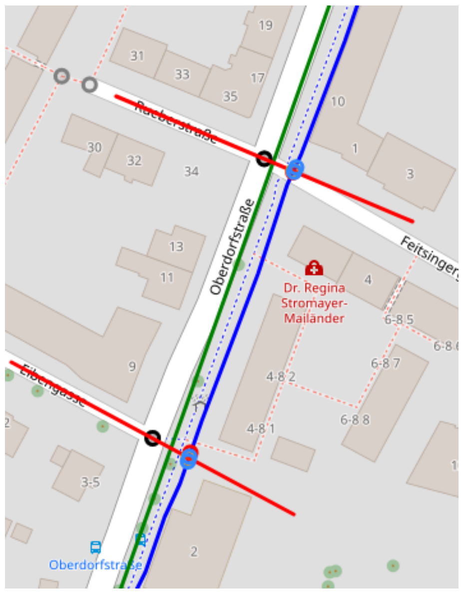

Figure 29: The route (*blue* line) passes two intersections (*black* circles) here (*background*: *Leaflet*).

A person walks past an intersection and the route needs to be separated at the same "level" as the intersection. I aimed to create a slicing ray which lies parallel to the street that is crossed. To obtain this, all ways that are connected to the junction point are retrieved, the adjacent nodes determined and vectors between the junction point and the adjacent nodes calculated. From these vectors, the one with minimum angle θ is chosen:

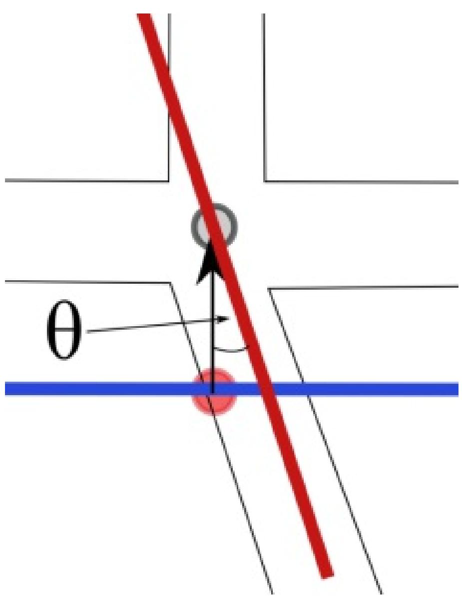

Figure 30: The junction point is projected onto the route (*red* circle). We want to minimize the angle between the normal vector and the slicing ray (*red* line) (*background*: OpenStreetMap contributors (2017)).

This procedure was unfortunately not sufficient for all cases. There were two situations which had to be handled differently: The first one occurred often at a turning point.

Figure 31: (*background*: OpenStreetMap contributors (2017)).

In the example above the "slicing" ray intersects the route further away from the intersection. In such situations, the intersection was simply projected onto the route. Secondly, sometimes the GPS track had low quality and despite minimizing θ (Figure 31), the slicing ray was oriented differently.

I implemented the algorithm in such a way that it would allow this step-wise procedure and therefore, defining junctions which should be excluded, included and allow to decide how a route is partitioned (projection, reorientation of slicing ray) at each junction.

E. Data Analysis

In this work, a binary classification was conducted using Generalized Estimating Equations (GEE). For this, the model building procedure followed guidelines by Hosmer Jr et al. (2013) and additionally, the application of the variance inflation factor was introduced to avoid multi-collinearity within the model (Akinwande et al., 2015).

During the model building, it has been observed that variables related to the POI densities would be significant. There are a lot of POI density variables due to the variety of possible POI tags and values these tags can have. Due to this, most POI density variables have value 0 for most observations. It was suspected that this might induce overfitting in the model. Further, I realized that the POI density variables are not entirely independent between each other as a POI object has usually more than one tag and one tag with a specific value might determine that another tag is present (e.g. a coffee shop which has tag *amenity* with value *cafe* and therefore also tag *shop* with value *coffee*). These observation led to the following the decision: Only POI density variables of one tag could be included because of the independence assumption between "independet" variables. The tag *amenity* was chosen because it is frequently used in tagging of OSM POI data and during modeling, POI densities related to *amenity* showed significance. To avoid overfitting, a grouping within this class was conducted carefully based on the associated appearance of the objects and their usage. This procedure yielded the following POI density variables summarizing point density of multiple values for tag *amenity*:

- Gastronomy :*amenity_gastronomy* summarizes density values of tag-value pairings *'amenity':'restaurant', 'amenity':'bar', 'amenity':'brothel', 'amenity':'cafe', 'amenity':'fast_food', 'amenity':'ice_cream', 'amenity':'nightclub', 'amenity':'pub', 'amenity':'swingerclub'*

- Street furniture: *amenity_street_furniture* summarizes density values of tag-value pairings *'amenity':'bench', 'amenity':'public_bookcase'', 'amenity':'post_box, 'amenity':'drinking_water', 'amenity':'lost_property_box', 'amenity':'clock', 'amenity':'fountain', 'amenity':'scale', 'amenity':'waste_basket', 'amenity':'toilets', 'amenity':'vending_machine', 'amenity':'telephone'*

- Mobility infrastructure: *amenity_mobility* summarizes density values of tag-value pairings *''amenity':'bicycle_parking', 'amenity':'bicycle_rental', ''amenity':'bicycle_repair_station', ''amenity':'car_sharing', 'amenity':'charging_station', 'amenity':'fuel' 'amenity':'taxi', 'amenity':'parking', 'amenity':'parking_entrance', 'amenity':'compressed_air'*

- Educational institutions: *amenity_edu* summarizes density values of tag-value pairings *'amenity':'childcare', 'amenity':'driving_school', 'amenity':'kindergarten', 'amenity':'lecture_hall', 'amenity':'music_school', 'amenity':'university', 'amenity':'auditorium', 'amenity':'school'*

- Health facilities: *amenity_health* summarizes density values of tag-value pairings *'amenity':'dentist', 'amenity':doctors, 'amenity':'veterinary', 'amenity':'healthcare', 'amenity':'pharmacy'*

- Cultural facilities: *amenity_culture* summarizes density values of tag-value pairings *'amenity':'community_centre', 'amenity':'arts_centre', 'amenity':'cinema', 'amenity':'social_facility', 'amenity':'theatre'*

After this, these were the main steps that led to the final model:

- Variable selection
- Elimination of mutli-collinearity
- High-dimensionality reduction
- Testing of previously omitted variables
- Obtaining main effects model
- Introduction of interaction terms
- Testing of model stability

Variable selection The variable selection followed the suggestions of Hosmer Jr et al. (2013)[4]: variables where selected first based on the *Pearson chi-square test* and *continuous* variables further through applying uni-variable model fitting. The significance level of 0.25 was set for the screening process. These resulted in seven categorical and 27 continuous features for further modeling. Moreover, to prevent overfitting, variables who where representative for $< 5\%$ of the observations were excluded. Further,

[4]Being well aware that this work is aimed for logistic regression, I chose to use this procedure as I was not able to find model building procedures suggested explicitly for GEE in a similar manner.

"duplicate" variables which hold same information had to be excluded, e.g. either *condition_unfamiliar* or *condition_familiar* could remain.

Elimination of multi-collinearity I followed here an iterative approach of elimination of variables inducing multi-collinearity which means that a model was calculated, then VIF values were obtained and the variable with maximum VIF was excluded. Then, a new model and new VIF values were computed and again the maximum value of observed. This procedure was repeated until VIF values of all variables were < 5.

High-dimensionality reduction In this step, variables were one-by-one removed from the model while the effect of the removal on coefficient values, p-values and, most importantly, the change of Quasi-Likelihood Criterion (QIC) was observed. Hosmer Jr et al. (2013) suggested that changes in magnitude of coefficients of at least 20% would be crucial. Throughout this procedure, I reduced the model to seven variables. During this reduction process, I kept an eye on the variables with a highly fluctuating coefficient magnitude. within the process omitting these improved the model fit.

Obtaining main effects model Hosmer Jr et al. (2013) suggested to test the assumption of the linear relationship between the logit of population mean and the covariate. This was done graphically as described by Hosmer Jr et al. (2013). In this process, the influence of only one variable was changed (*amenity_health* was changed to a dichotomous one).

Introduction of interaction terms Hosmer Jr et al. (2013) suggests to first think of possible and reasonable interaction terms and then test them. According to the author, an interaction term should only be included if it is significant by itself and only if the interaction is clinically reasonable. Before testing interaction terms, I decided to limit the testing to interactions between personal variables and route-related or behavioral variables. Throughout the testing, multiple interaction terms improved the QIC but most of them were either not significant by themselves within the model or introduced high VIF values. Therefore, only one was included in the final model.

Testing of model stability Lastly, I had to ensure that the significance of the covariates would be not caused by singular observations. For this, I calculated the Cook's distance for all observations, identified top ten influential observations and observed the model parameters while removing one-by-one. The model parameters stayed consistent with only minor changes throughout this procedure.

F. Availability of Data and Processing Scripts

All experiment data is available here: `G://geo/geoinfo/Data/all_experiment_Data` in path `G://geo/geoinfo/Data/GOLAB_Diplomarbeit`, the following processing scripts are available (last edit 01/02/2020):

`/Android application/ ...`

`/Experiment_app/ ...  Java Android application used to logg times of requests during experiment`

`/Sensorlogger/ ...  Java Android application which records or internal phone sensors`

`/OQ/ ...`

`/data/raw/database ...  csv-files and sql-dumps of database with familiarity data collected during the online questionnaire`

`/data/raw/limesurvey ...  file to recreate Survey and all answers`

`/Participant data/ ...  processing scripts for questionnaires and final table with final participant variables`

`/Preparation of Experiment/ ...`

`/route_matching/ ...  script for matching routes to trials in unfamiliar condition`

`/landmark_algorithm/ ...  scripts for obtaining landmarks; instruction written down in readme.txt; + example outputs`

`/Experiment data processing/ ...`

`/DB/ ...  holds data which is needed for segmentation`

`/synchronization/ ...  script used to synchronize all devices to GPS time and final file with synchronization for all trials`

`/navigation_instructions/ ...  information on navigation instruction for all trials`

`/segmentation/ ...  all scripts to yield`

`/data/ ...  folder data resulting from the segmentation process`

`/htmls/ ...  visualizations of click location and segmentation for all trials`

`/shape_file/ ...  routes which were drawn to compensate for bad quality of GPS track`

`segmentation_stats.csv ...  key file for conduction of segmentation, holds all information of turning points, intersections, etc for all trials` presentation_terminology_explanation.pdf ... presentation with illustrations for explanation of most important terminology and variables

extract_segment.py ... holds function which assists in choosing appropriate intersections for segmentation

extract_segment_info.py ... partitions the route and relates times of requests to positions

unify_linestrings.py, unify_all_info.py ... create united segments

model_1_join_segments_step_1.py, model_1_segments_del_visible_dest.py ... create data describing position of first request

save_gps_data_to_db.py, viewshed.py ... hold functions for visibility analysis and GPS track data processing

/environmental feature extraction/...

/database/ ... all data which is needed to retrieve environmental data

pois_density.py ... for retrieval of all POI density variables for a linestring

segments_landcover.py ... used to retrieve land cover shares for a linestring

/GEE analysis/ ...

variable_transfo.py ... prepares all features

GEE.R ... GEE model building

/data/ ... all needed data for GEE analysis

G. Submitted paper of version

On the following pages, the original paper on which this work is build can be found. It was submitted on November 30^{th}, 2020 to a special issue of the journal *Spatial Cognition and Computation*.

It's also about timing! When do pedestrians want to receive navigation instructions

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November 30, 2020

Abstract

Wayfinding assistance systems have seen increased interest over the last two decades. However, research on the appropriate point in time to automatically present a route instruction has been very rarely conducted. We address this research gap by reporting on the results of an in-situ, within-subject-design wayfinding study ($N = 52$). Participants walked two different routes for which they requested auditory, landmark-based route instructions. By means of a survival analysis we model the points in time at which participants issue such requests, considering personal, environmental, route and trial related variables and reveal different landcover classes and personal variables to be important. Based on our model-driven results, we discuss potential reasons for the impact of these variables and derive open research question.

1 Introduction

Navigation is an intrinsically complex task, during which "[t]he navigator is continuously busy in a sequential process of decision making whose essence is to match internal with external information as it comes"(Stern & Portugali, 1999, p. 99). Given this complexity, research on decreasing the cognitive load of wayfinders by means of mobile assistance systems has seen much interest for more than 20 years (see, e.g., Coors, Elting, Kray, & Laakso, 2005; Geldof & Dale, n.d.; Millonig & Schechtner, 2007, for early attempts). However, almost all of these studies neglect the problem of providing the route instruction at the right point in time: Users of wayfinding assistance systems are supposed to either choose the suitable point in time themselves or route instructions are given based on distance-based algorithmic approaches ignoring personal variables as is the case for commercial systems. This system behavior, however, is likely to result in increased cognitive load which has been pointed out, for example, by Winter (2003). The present paper reports on the first within-subject design, in-situ study designed to understand the points in time/locations at which users would actually need auditory landmark-based route instructions. In doing so, we use Giannopoulos, Jonietz, Raubal, Sarlas, and Stähli (2017) as a starting point of our study, as they present the first in-depth study of timing for pedestrian navigation systems in a virtual environment, as a starting point. While the empirical setup had to be slightly adapted due to the in-situ nature, we have taken the opportunity to consider an increased number of variables, relating to personal, route-related and environmental factors. We have, however, chosen to apply the same data analysis method as Giannopoulos et al. did: The model they utilised is a time-to-event model, which is suitable to address the problem of predicting when a system should automatically present navigation instructions. At the same time, it is not a so-called black-box as, e.g., machine learning approaches would have been.

2 Related Work

According to Montello (2005), navigation comprises two activities, wayfinding and locomotion. While locomotion describes the movement of one's body through the environment and includes tasks like avoiding obstacles, wayfinding encompasses route planning and all related decision-making processes to reach a given destination. During navigation, we constantly receive information about our physical environment through our senses and need to connect it with our knowledge to update our location and determine future decisions along our route. Theoretical reasoning and empirical evidence (see, e.g., Fang, Li, & Shaw, 2015; Giannopoulos, Kiefer, Raubal, Richter, & Thrash, 2014; Schmidt, Beigl, & Gellersen, 1999), therefore, suggests that a wayfinder's cognitive load is impacted by personal characteristics, the environment and the actual route through this environment. Reducing the users' cognitive load is, hence, one of the major aims in designing wayfinding assistance systems. Scholars have pursued this objective by means of working (1) on the content, structure and presentation of route instructions and (2) adapting wayfinding systems to the user's personal needs. In this section, we will review both strands of prior work and, thereby, provide evidence for a lack of research on timing of route instructions, in particular for pedestrian navigation systems.

2.1 Research on Route Instructions

While distance-based, on-line turn-by-turn instructions have been predominant in commercial applications, researchers have put emphasis on understanding the way humans communicate route instructions in order to mimick this way in wayfinding assistance systems for many years. Research on verbal human-to-human communication of route instructions and it's underlying cognitive processes (see, e.g., Hölscher, Tenbrink, & Wiener, 2011) revealed that landmarks are used frequently (see, e.g., Lovelace, Hegarty, & Montello, 1999; May, Ross, Bayer, & Tarkiainen, 2003; Michon & Denis, 2001) across different spatial environments (see, e.g., Sarjakoski et al., 2013, for hiking instructions). Empirical evidence has been provided that the use of landmarks has a positive impact on wayfinding performance (see, e.g., Ross, May, & Thompson, 2004; Tom & Denis, 2004) and that the absence of landmarks in an environment is compensated by an increased granularity of verbal human-to-human route instructions (see Hirtle, Richter, Srinivas, & Firth, 2010). Research on including landmarks (see Richter & Winter, 2014, for a thorough overview of the concept) in route instructions for wayfinding assistance systems has, consequently, become a predominant research topic, including modeling (see, e.g., Caduff & Timpf, 2008; Nothegger, Winter, & Raubal, 2004; Nuhn & Timpf, 2017; Raubal & Winter, 2002; Winter, 2003), empirical assessment (see, e.g., Götze & Boye, 2016; Kattenbeck, 2017; Kattenbeck, Nuhn, & Timpf, 2018; Quesnot & Roche, 2015) of salience and the automatic selection of landmarks (see, e.g., Duckham, Winter, & Robinson, 2010; Lander, Herbig, Löchtefeld, Wiehr, & Krüger, 2017; Lazem & Sheta, 2005; Rousell & Zipf, 2017; Wang & Ishikawa, 2018).

Beyond the focus on important elements in human-to-human route instructions, researchers have worked on the formulation of route instructions in wayfinding assistance systems. The concept of *spatial chunking* (Klippel, Tappe, & Habel, 2002) has been of particular importance in these endeavours, as it reduces the cognitive load in wayfinders by reducing the level of granularity in route instructions. This idea was picked up algorithmically (see, e.g., Richter & Klippel, 2005) and resulted in guidelines for cognitively ergonomic route directions (Klippel, Richter, & Hansen, 2009) which take, e.g., different levels of hierarchical spatial knowledge. In line with these guidelines empirical evidence also suggests that the granularity of route instructions increases in human-to-human route instructions if wayfinding decision situations lack landmarks (Hirtle et al., 2010). As the body of knowledge on adverse effects of wayfinding assistance systems on spatial knowledge acquisition grows (see, e.g., Ishikawa, 2019), scholars have also studied ways to overcome this issue. One very recent advancement in this domain are so-called orientation instructions (Schwering, Krukar, Li, Anacta, & Fuest, 2017) which enhance spatially chunked instructions by including additional environmental information to support acquisition of route and survey knowledge (see Krukar, Anacta, & Schwering, 2020, for empirical evidence that these instructions are superior to turn-by-turn or spatially chunked instructions without additional information).

Neither the research efforts on landmarks nor on formulating route instructions reflect on how timing of a route instruction would have an impact on these. This lack of consideration holds also true for research on modalities and presentation of route instructions. Beyond the prevalent map-based approaches, reaserch on modalities and presentation modes has primarily focused on their impact on wayfinding effectiveness and efficiency by studying, for example augmented photographs (see, e.g., Walther-Franks & Malaka, 2008; Wang & Ishikawa, 2018), audio (e.g. Holland, Morse, & Gedenryd, 2002), augmented reality (see, e.g., Rehrl, Häusler, Leitinger, & Bell, 2014), vibro-tactile signals (see, e.g., Giannopoulos, Kiefer, & Raubal, 2015), and even music (see, e.g., Hazzard, Benford, & Burnett, 2014). Recently, however, studies on the presentation of instructions have also considered the reduction of attentional load (see, e.g., Stähli, Giannopoulos, & Raubal, 2020) and effect on spatial knowledge acquisition (see, e.g., Brügger, Richter, & Fabrikant, 2018).

2.2 Research on personalisation of wayfinding assistance systems

Optimal wording, choosing the most suitable landmark among a set of candidates and the ideal presentation mode can, beyond general solutions, depend heavily on user characteristics. Personalisation of wayfinding assistance systems has, consequently, seen increased interest. Researchers (see, e.g., Klippel et al., 2009; Zimmer, Münzer, & Baus, 2010) developed frameworks for the design of navigation aids emphasising the adaption to user characteristics like spatial familiarity and spatial abilities. Empirical evidence has been collected for the increase in wayfinding performance through adaptation of, e.g., the presentation of route instructions to sense of direction (see, e.g., Bienk, Kattenbeck, Ludwig, Müller, & Ohm, 2013). Personal interests have also been incorporated into salience models, in order to be exploited for choosing personalized landmarks (see Nuhn & Timpf, 2020). Moreover, a large branch of research is dedicated to adapting systems to users with special needs, such as mobility impaired people (see, e.g., Barhorst-Cates, Rand, & Creem-Regehr, 2019; Cheraghi, Almadan, & Namboodiri, 2019) or visually compromised (see, e.g., Ding et al., 2007; Völkel & Weber, 2008) persons.

2.3 Timing

So far, we have seen considerable effort dedicated to optimizing pedestrian wayfinding assistance systems with respect to the structure, granularity and presentation of route instructions, as well as adapting it to user's personal preferences and needs. All of these research efforts, however, neglect — with exception of Giannopoulos et al. (2017) — the key question of presenting a navigation instruction to a pedestrian at the right point in time. This is, on the one hand, in contrast to the attention timing has seen in research on car navigation systems (see below); on the other hand, it is also in contrast to empirical evidence (see, e.g., Brügger, Richter, & Fabrikant, 2019, who provide strong evidence for the way system behavior and wayfinder behavior interact) and theoretical claims. In their theoretical account based on Maslow's theory, Fang et al. (2015) emphasise the importance of the inclusion of personal preferences to be able to predict their behavior and to make pedestrians feel more comfortable by adjusting navigational instructions and interaction load with the navigation system as a response to the dynamic change of environment. This hints towards the importance of research on which factors influence the preferred timing of navigational instructions based on the user's personal preferences. Despite the fact that timing of route instructions is a desideratum with respect to pedestrian wayfinding, it has seen much interest in car navigation systems. This fact has been also stated by Giannopoulos et al. (2017), who present the first study on timing of pedestrian navigation instructions. As a starting point, the authors thoroughly reviewed literature on timing in car navigation systems and found several variables to be important: environmental factors (traffic, visibility of road signs), driver's characteristics (age, gender), driving speed and attributes of the navigational instruction (length, upcoming turn/manoeuvre). Subsequently, the empirical part of their study, which was conducted in a virtual environment, found similar factors which influence user preferences in timing of pedestrian navigational instructions (see Giannopoulos et al., 2017, p. 16:9): These include personal characteristics like age and spatial abilities and route specific aspects such as the shape of the upcoming intersection, its visibility or the length of the route segment. Their findings are in line with empirical evidence that wayfinders make spatial decisions before the arrive at an intersection (see Brunyé, Gardony, Holmes, & Taylor, 2018) and accounts for the impact personal and spatial characteristics of the environment have on the complexity of wayfinding decision situations (Giannopoulos et al., 2014).

Based on these considerations, the goal of the present study is to build on these results and study preferred timing of route instructions in-situ based on personal, environmental and route-related characteristics. These results will shed light on how the appropriate points in time to present a route instruction automatically can be determined considering these variables.

3 Experimental Design and Procedure

This section provides a detailed account of the experimental design and procedure of the in-situ study on which our work is based. It is important to note, that the experiments were part of a larger data collection effort. We will, therefore, only explain those parts of the design and procedure that are needed to reproduce the results of this paper.

3.1 Materials

The entire experiment consisted of two parts. The first part contributed to the design of route instructions for the in-situ study, the second part was the in-situ study itself which took place between June and October 2020.

3.1.1 Acquisition of routes

We collected routes for our study by means of an online questionnaire during which we also collected demographic data, data on spatial strategies (FRS, Münzer & Hölscher, 2011) and personal characteristics based on the so-called Big Five Personality traits (Rammstedt, Kemper, & Céline, 2013). To collect routes, participants were asked to outline areas in Vienna they are familiar with using polygons as well as highlight and name places they know within these polygons. In order to ensure a reasonable experimental time, two of these places were randomly selected on the condition that they are 900m to 1.3km apart. One place of these served as a starting point, the other one was set as the destination and these roles were randomly assigned. Subsequently, we asked participants to sketch the route they would choose between these two points. Although there has been research concerning the selection of representative routes for wayfinding experiments (Mazurkiewicz, Kattenbeck, Kiefer, & Giannopoulos, 2020) we, subsequently, asked our participants to sketch the route between these two places in order to ensure familiar routes.

3.1.2 Generating auditory route instructions

In order to design landmark-based route instructions, we used the algorithm described by (Rousell & Zipf, 2017) to identify a ranked-list of landmarks at each turning point (see section 3.2 for the reason of this decision). We implemented this algorithm using `Python 3.8` and the *OSMNX*-library (Boeing, 2017) to retrieve building footprints and the street network. Subsequently, the experimenter visited each of the routes in person and checked the selected landmark for potential ambiguities due to, e.g., cases of inconsistent and incomplete Point of Interest (POI)-data in OpenStreetMap (OSM). This in-situ check ensured the suitability of the suggested landmarks thereby avoiding confounding effects stemming from confusion due to the use of unsuitable objects in route instructions. Based on the revised set of POIs we have built the German language route instructions by analogy with Rousell and Zipf (2017) as can be seen by the following example (translation: *Turn left at the pharmacy*):

General structure	Imperative to turn	landmark	direction of turn
Example in German	*Biegen Sie bei*	*der Apotheke*	*links ab.*

The resulting route instructions were synthesized using *Google Cloud Text-to-Speech Engine* (Google Inc., 2020).

3.2 Procedure

The in-situ study was designed as a within-subjects design study during which each participant walked two different routes: One of these was provided by the person during the online data collection phase, whereas the other route was provided by another participant. We will refer to walking one of the routes as trial throughout this text.

During each of the trials, trajectories were collected using a high precision GNSS receiver (PPM 10-xx38, see figure 1), participants wore bluetooth earphones to receive auditory route instructions and requested route instructions through a custom-built clicker device. In addition to that, head (xSens MTi-300 IMU) and eye movement data (PupilLabs Invisible) was collected but not used in the current study as we wanted to study the impact of those variables which are independent of specific equipment.

Before the start of each trial, participants were carefully instructed to press the button of the clicker to request a route instruction whenever and as often as they wanted to. They were, moreover, made explicitly aware of the fact that they will be given landmark-based route instructions by

Figure 1: **A:** A sample participant in full equipment. **B:** GNSS receiver (PPM 10-xx38). **C**: During the experiment, participants requested navigation instructions using a custom-built clicker-device (circled in red) which triggers a LED light located in the backpack informing the experimenter about the request.

means of an example which was not part of the actual route. As mentioned above, we provided route instructions exclusively at turning points, a decision which is in line with the idea of spatial chunking (Klippel et al., 2002) and increases ecological validity as the majority of state-of-the-art wayfinding assistance systems provides route instructions only for turning points. As a consequence of this decision, participants were instructed, that once they requested an instruction, the received instruction might not be relevant for the upcoming intersection, i.e., the participants would have to continue walking straight ahead until they find the intersection were the instruction can be matched with the environment. In order to avoid memory biases about the routes participants had provided during the online data collection phase, they were explicitly asked to request and strictly follow the route instructions. On start of the trial, the experimenter pointed participants to the direction in which they should start walking. Whenever participants requested a route instruction, the experimenter played the spoken landmark-based route instruction for the upcoming turning point to them via the Bluetooth-connected earphones. This point in time was logged by a smartphone application running on a mobile phone carried by the experimenter.

4 Analysis

4.1 Data availability

The (pre-)processing scripts as well as the raw data used in this paper will be made available through the zenodo.org platform via the DOI `10.5281/zenodo.4298703` in order to facilitate reproducibility of the results.

4.2 Data preprocessing

Experiments were conducted between June and October 2020[1]. Participants were acquired through personal contact, posts on social media platforms and leaflets; they were reimbursed through a lottery. Overall, $N_r = 71$ people registered on our website and, of these, $N_p = 52$ persons (female: 25 , male: 27 , $M_{age} = 26.2$, $Median_{age} = 24$) completed both experiment parts. This results in an overall number of $N = 104$ trials. Applying a case-wise deletion approach, we had to exclude 18 trials, e.g., due to data loss by equipment malfunction. This leads to a final number of $N = 86$ trials to be included in the further analysis.

4.2.1 Segmentation of Data

Finding meaningful route segments was the essential preprocessing part for our data analysis. Figure 2 provides an overview of the algorithm which was based on OSM data. Black circles represent the location of intersections according to OSM; the smoothed GPS track of a trial is given in blue, the yellow circles represent the projection of the intersections on this line and the locations at which a participant requested a route instruction are given as green circles. It is important to note that we found segments based on the actual user behavior instead of using the mere distance between two intersections, i.e., subsequent yellow circles. This decision is based on the fact that due to the structure of the environment not all intersections may be perceived as decision points by pedestrians. Each segment starts at a major route point, i.e., either at the starting point or at an intersection to which the previous route instruction referred to. A segment ends at the first intersection along the route after a participant has requested a route instruction for the first time.

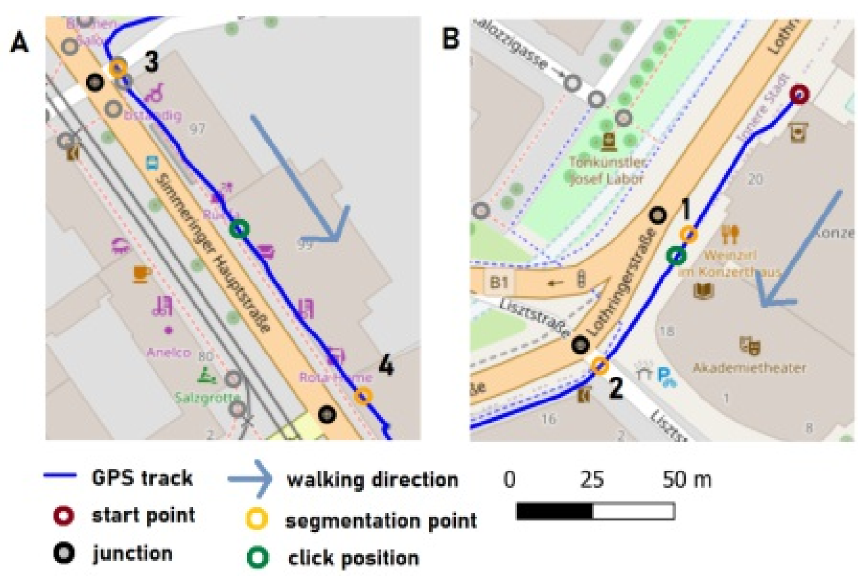

Figure 2: Segmentation process. Two possible situations: **A** (regular case): The segment starts at the last turning point denoted as *3*. The first intersection after the click position is denoted as *4* and the segment ends at the segment ends at this intersection.
B: A route segment covering the distance from the starting point to intersection *2*. Intersection *1* is ignored because the instruction is requested after it was passed, i.e., the participant has not perceived it as a decision point.(*background*: Story (2013))

This procedure yielded $N_{iseg} = 314$ segments. Further data cleaning procedures were required

[1] Due to the COVID-19 pandemic, participants were harder to find than usual.

to exclude segments on which the person was able to see the destination from the position of the request (25 cases), the experimenter played the instruction to the participants because they missed the turning point (10 cases) and those segments on which requests were made before entering the new route segment (35 cases) as this is situation not covered by survival analysis models. Finally, we had to remove one outlier during the modeling stage, resulting in $N_{cseg} = 245$ segments available for analysis.

4.2.2 Overview of data available for analysis

The table provided as supplementary material to this article contains a description of all variables which were derived from the data, including their type, unit and whether it is a derived attribute (and, if applicable, the source it is derived of). Based on the data collected, we have calculated $N = 50$ which can be grouped into five categories: ***r**oute*, ***p**articipant*, ***e**nvironmental*, ***t**rial* and ***b**ehavioral* level. This decision is in-line with prior work on wayfinding decision situations (Giannopoulos et al., 2014), which provides theoretical explanations and empirical evidence that these variables have an impact on the perceived difficulty of a decision situation. These aspects are, hence, likely to have an impact on timing. *Route* features comprise aspects relating to the route itself, e.g., the length of each route segment, the type of each intersection and so on. Features relating to the *participant* include demographics such as age and gender but also measures of their preference in spatial strategies by means of the FRS scale (Münzer & Hölscher, 2011) and a short version of the Big-Five-Inventory (Rammstedt et al., 2013), giving an insight into their personality traits. The reason to choose the FRS scale instead of the Santa Barbara Sense of Direction Scale (Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002) is based on the assumption that preferences/abilities for different spatial strategies (global/egocentric or allocentric as well as the knowledge of cardinal direction) may provide a means to further explain timing results: For example, participants with better egocentric abilities may prefer, e.g., later points in time than people with good allocentric orientation do. Group *environmental* covers all variables which are suitable to describe the environment the routes were embedded into, e.g. the density of POIs at an intersection or the land cover classification for segments. Finally, the *behavioral* class encompasses all features relating to the requests of route instructions by participants (e.g., of course, the point in time of the click itself, but also aspects such as the distances to the previous and upcoming intersections etc.).

4.3 Survival Analysis Model

Generally speaking, the modeling of duration data aims at identifying what affects the underlying processes in order to be able to draw conclusions about the type and magnitude of impact that different variables exert on it, and, hence, provide the ability of making predictions when needed. In this regard, regression models constitute a way of assessing and evaluating those impacts. Driven mainly by advances in the biomedicine domain, a family of models called *survival analysis models* have been proposed (see Hosmer Jr, Lemeshow, & May, 2011; Kalbfleisch & Prentice, 2011, for a detailed overview); these show methodological and conceptual advantages over traditional regression approaches (see, e.g., Bhat & Pinjari, 2007). In brief, these models perceive duration as a survival process and center their focus on the share of individuals that survive past a given (time) point. A focal element of those models revolves around the notion of hazard, i.e., the rate at which the duration process changes over time.

The application of survival analysis models in spatial settings was explored and exemplified for the first time by Waldorf (2003). A number of applications have built upon that work and utilized such models for tackling distance-related questions such as trip length modeling (see, e.g., Anastasopoulos, Islam, Perperidou, & Karlaftis, 2012; Sarlas & Axhausen, 2018).

Among those models and for cases which focus primarily on prediction, choosing fully parametric models is most appropriate as these fully describe the basic underlying survival distribution and, at the same time, quantify how this distribution changes as a function of the explanatory variables (Hosmer Jr et al., 2011). Two categories of such models exist, namely the proportional hazard and the accelerated failure time (AFT) models. These differ with respect to the assumptions of how the survival function is affected by the explanatory variables. While the former assume that the explanatory variables have a constant multiplicative effect on the underlying hazard function, this relationship is assumed to be also multiplicative on the time scale by the latter.

By analogy with Giannopoulos et al. (2017), we focus exclusively on estimating an AFT model as it is reasonable to assume that the relationship of the explanatory variables is multiplicative on time. T represents the timing or distance of instructions for an individual with a cumulative distribution function $F(t) = Pr(T \leq t)$. The survival function represents the probability of observing a survival distance higher than t, denoted as $S(t) = \Pr(T > t) = 1 - F(t)$. Subsequently, the hazard function, defined as the probability of a process ending at point t given that it has lasted up to point t, is as follows:

$$h(t) = \frac{\mathrm{f}(t)}{S(t)} \tag{1}$$

Essentially, the knowledge of either function (i.e., $f(t)$, $F(t)$, or $h(t)$) allows the direct inference of the remaining two. In case of the AFT models with a Weibull survival function, T is defined as $T = e^{\beta_0 + \beta_i x} * \varepsilon$, with β's representing the effect of explanatory variables x_i, and an error component ε.

Applying a log transformation results in:

$$ln(T) = \beta_0 + \beta_i x_i + \sigma * \varepsilon^* \tag{2}$$

with $\varepsilon^* = ln(\varepsilon)$ following the extreme minimum value distribution, denoted as $G(0, \sigma)$ with σ being the scale parameter. The corresponding hazard and the survival function are:

$$h(t, \chi_i, \beta_i, \lambda) = \frac{\lambda t^{\lambda-1}}{\left(e^{\beta_0 + \beta_i x_i}\right)^{\lambda}} = \lambda t^{\lambda-1} e^{-\lambda(\beta_0 + \beta_i x_i)} = \lambda\gamma \left(t e^{-\beta_i x_i}\right)^{\lambda-1} e^{-\beta_i x_i} \tag{3}$$

$$S(t, \chi_i, \beta_i, \sigma) = exp\{-t^{\lambda} exp[(-1/\sigma)(\beta_0 + \beta_i x_i)]\ \} \tag{4}$$

with$\lambda = 1/\sigma \ and \ \gamma = exp(-\beta_0/\sigma\ )$. With this formulation, the equation for the median survival time can be derived by setting $S = 0.50$:

$$t_{50}\left(\chi_i, \beta_i, \sigma\right) = \left[-ln\left(0.5\right)\right]^{\sigma} e^{\beta_0 + \beta_i x_i} \tag{5}$$

Formula (2) shows that the β's quantify the effect of the explanatory variables on T, which can, for this case, be interpreted as semi-elasticity values, i.e., 100*β_i is the approximate percentage change on T for a unit change on x_i. However, that change is not constant along the corresponding survival function (see 4). Based on formula (5), the impact of a change on x_i on its median T is given by:

$$TR\left(x_i, x_i'\right) = \frac{t_{50}\left(x_i', \beta_i, \sigma\right)}{t_{50}\left(x_i, \beta_i, \sigma\right)} = \frac{\left[-ln\left(0.5\right)\right]^{\sigma} e^{\beta_0 + \beta_i x_i'}}{\left[-ln\left(0.5\right)\right]^{\sigma} e^{\beta_0 + \beta_i x_i}} = e^{\beta_1 \Delta x_i} \tag{6}$$

5 Asking for an instruction for the first time after a turn — Results

As mentioned above, the auditory route instructions were landmark-based, exclusively referred to turning points and could be requested as often as participants wished to do so. Given this setup we proceed with the estimation of an AFT model describing the distance at which participants ask for a route instruction for the first time after they have passed the last turning point. The modeling results will be suitable to predict when a system should automatically present a route instructions to users.

Table 1: Influential variables in model. **levels:** P: participant, R: route, T: trial, E: environment **sources:** OQ: online questionnaire that was completed by participants, UA: *Open Street Map*,OSM: OSM. Readers may want to refer to the supplementary material for further details on these.

level	variable	description	type	unit	source
P	age_gt_40	age greater than 40	dichotomous	N/A	OQ
	BFI_o_low	result of subscale openness of BFI-10 scale; threshold <3.41 according to norm data(see Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2012, p. 28)	5-point likert scale	N/A	OQ
	SOD	sense of direction derived from FRS questionnaire	7-point likert scale	N/A	OQ
	EGO_lt_three	factor EGO derived from FRS questionnaire	7-point likert scale	N/A	OQ
R	lngSegm	segment length >120m This threshold was found empirically, i.e. evaluated based on lower and upper quartile of the segment length and different thresholds were tested to classify short and long segments, respectively. However, only long segments yielded a significant effect.	metric	meter	
T	familiar/unfamiliar	participant is familiar/unfamiliar with route and environment	dichotomous	N/A	OQ
E	LC_*	land cover share of 50m buffer around route segment 1 = 12100; 2 = 1110 + 11210 12100, 1110, 11210 ... landcover codes of Urban Atlas (European Comission, 2012)	metric	%	UA

The model focuses on when the first request for instructions was triggered by the participant. Those requests, though, have two conjoint dimensions, a temporal and a spatial one while they are naturally bound by the length of the segment per case. For this reason, we choose to focus exclusively on the spatial dimension of the matter. Therefore, the dependent variable of interest is the distance between the start of a route segment and the position at which a request for a navigation instruction is made. We apply a normalization to the range of [0,1] by division by the segment length per case, in order to have a uniform duration period for all observations which is a prerequisite for the model estimation that follows.

Subsequently, an AFT model is estimated with a Weibull duration distribution in place, similarly to the one presented in formula (4). The calculations were conducted using the open-source statistical software R (Core Team et al., 2013), exploiting version 3.2-7 of the *Survival* package

Table 2: Summary statistics of the observations used for model estimation. *(d)* denotes a dichotomous variable; for these variables column mean represents the proportion in the sample.

Statistic	Mean	St. Dev.	Min	Max
distance norm.	0.494	0.333	0.004	1.000
segment length	80.794	58.600	4.516	426.500
length_long (d)	0.143	-	-	-
age	26.596	9.001	18	59
age_gt_40 (d)	0.073	-	-	-
LC_1	0.129	0.179	0	1
LC_2	0.427	0.287	0.000	0.900
LC_3	0.090	0.214	0	1
familiar (d)	0.420	-	-	-
unfamiliar (d)	0.580	-	-	-
SOD	4.822	1.468	1.920	6.911
EGO	3.595	1.099	0.478	6.216
EGO_lt_three (d)	0.314	-	-	-
BFI_o	3.520	1.074	2	5
BFI_o_low (d)	0.424	-	-	-

(Therneau, 2014). The choice of the form of the parametric survival function is made based on the Akaike Information Criterion (AIC). More specifically, the resulting model is estimated in terms of maximum likelihood. Furthermore, standard errors are clustered accordingly to account for the dependence among observations stemming from the same individuals using a robust *sandwich* estimator.

The model specification involves the identification of which explanatory variables have a statistically significant impact on the outcome of interest. To a large extent, this process is driven by our assumptions about which characteristics of the person, route, trial and environment might influence the decision to request instructions. In particular, the explanatory variables are selected based on their ability to improve the fit of the model in terms of AIC (a metric that penalizes overfitting), along with the statistical significance of the corresponding parameters (p values). In addition to that, the absence of multicollinearity is ensured based on the calculation of the corresponding variance inflation factors which is required as multicollinearity would potentially invalidate the employed statistical tests and parameter estimation. The results of the parameter estimation along with the accompanied goodness of fit measures, are presented in Table 3, while the descriptive statistics of the employed sample are given in Table 2 and variables are explained in Table 1.

Table 3: Normalized timing of instructions based on the AFT model.

Variable	β	Robust std. error
age_gt_40	0.709***	0.173
LC_1	-0.541*	0.224
LC_2	-0.524***	0.138
LC_3	-0.352^{+}	0.184
BFI_o_low	-0.293*	0.121
unfamiliar:lngSegm	-0.712*	0.298
SOD:familiar	-0.046*	0.020
SOD:unfamiliar	-0.058**	0.018
EGO_lt_three:lngSegm	0.593**	0.205
Log(scale)	-0.314***	0.078
Scale σ	0.73	
Observations	245	
LogLikelihood	-43.5	
LogLikelihood (intercept only)	-62	
AIC	106.97	
p value: $+\ p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$		

Basically, obtaining the betas allows us to estimate the survival and hazard functions (see formulas 3 and 4) for different sets of explanatory variables, and, hence, individuals and spatial environments. Parameter interpretation can take place both in terms of sign and magnitude: An estimate with a positive sign implies a longer survival (i.e., instructions will be required at a later point in time), while a negative sign means the opposite. Concerning the magnitude, a quantitative interpretation can be made based on formulas (2) and (6). Based on the estimated parameters, we can obtain point estimates of quantiles of the distribution (e.g., the median) which are of potential interest for predicting the point in time at which a system should automatically present a route instruction.

When interpreting Table 3, one needs to keep in mind that the size of the parameters has to be taken into account in conjunction with the different value ranges of the variables. The coefficients in general have to interpreted ceteris paribus, i.e., the beta values show the impact of a variable on the condition that all other variables remain unchanged. In summary, the model comprises personal, environmental and route related variables, some of which are only rendered significant based on interactions with other variables. The obtained estimates indicate that participants requested a route instruction later as a function of their age (variable *age_gt_40*) and on segments longer than $120m$ if they belong to the group of people whose factor score for preference for egocentric orientation is below 3 (variable *EGO_lt_three:lngSegm*). All remaining variables describe an earlier request for an instruction: This holds for the two different classes of landcover (variables *LC_1* and *LC_2*) which are rendered significant at the 5% level, as well as for people scoring below average on the personality factor *openness* (variable *BFI_o_low*). In addition to that, if participants walk on long segments in an area they are unfamiliar with (variable *unfamiliar:lngSegm*), they request a route instruction earlier. Finally, sense of direction and familiarity interact with each other, i.e., depending on their sense of direction, wayfinders want route instructions earlier on familiar (variable *SOD:familiar*) and even more earlier on unfamiliar settings (variable *SOD:unfamiliar*). Figures 3, 4 and 5 provide further elaboration and interpretation of the model results:

In Figure 3, the median predictions (calculated based on formula 5) for the observations used for the model estimation are plotted against the actual ones. A strongly positive relationship between the two seems to be in place while their correlation is found to be equal to $\rho = 0.45$.

In Figure 4, empirical survival results are compared against predicted ones for two common cases identified in our sample having the following characteristics: $BFI\_o\_low = 1$, $lngSegm = 1$, and $age\_gt\_40 = 0$, i.e., people who are below 40 years of age, having a below average degree of openness and walk on long segments. The empirical survival function of those observations that correspond to a familiar setting are presented on the left, whereas the unfamiliar setting is shown on the right. The predicted mean survival functions have been obtained by making use of the estimated parameters and inserting the mean of the remaining explanatory variables into formula (4), with the exception of dichotomous variable *EGO_lt_three* which is set to 1. The figure illustrates that in both cases, the predicted mean survival rates are very close to the empirical ones while their 95% confidence interval values are always overlapping.

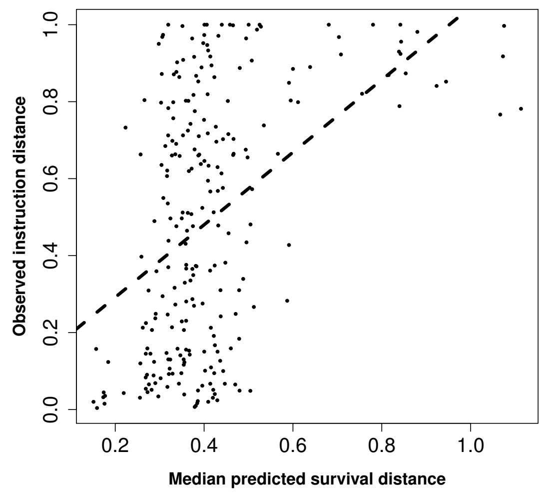

Figure 3: Predicted median survival values based on the estimated AFT model, compared against the observed ones.

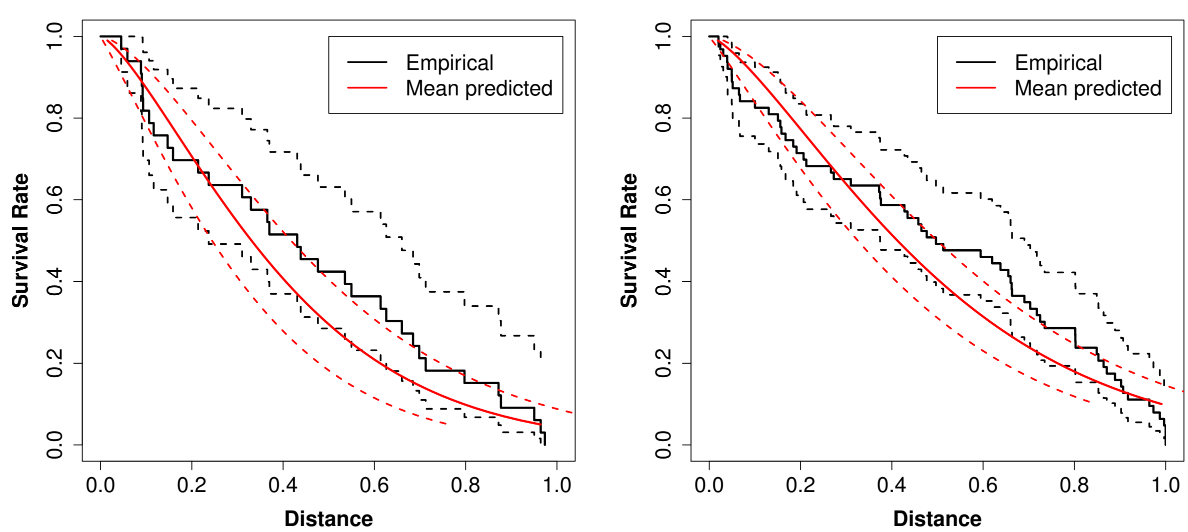

Figure 4: Empirical survival rates for two given subsets of observations (left: familiar, right: unfamiliar segments), compared against the mean predicted ones. Dotted lines represent the 95% confidence interval values.

Finally, the impact of the different explanatory variables on the predicted survival rates is demonstrated by modifying those variables accordingly, and plotting the resulting survival rates per case (Fig. 5). For that reason an artificial observation resembling a wayfinder with the following characteristics is defined as a base case, while for the remaining continuous variables the mean values of the sample are used (Table 2): $BFI\_o\_low = 0$, $lngSegm = 0$, $age\_gt\_40 = 0$, $EGO\_lt\_three = 0$, $unfamiliar = 1$, i.e. a person of less than 40 years of age, with a below average openness and very high preference for egocentric orientation, who walks on unfamiliar segments which are no longer than $120m$. The modification on the dummy variables consists of setting them to 1 (i.e. considering above average openness, long segments, older people, high preference for egocentric orientation or familiar segments); the continuous variables are modified by adding/subtracting a value equal to the respective standard deviation. On the left-hand side of the figure, the environmental and route characteristics of the base case are modified while on the right-hand side, the trial and personal ones are changed (see Table 1 for an explanation which variables these are). For instance, the black dotted line on the left side of the figure resembles the baseline artificial observation with an increase only in *LC_1*. Similarly, the red line resembles the baseline artificial observation with an increase only in *LC_2*. The blue line resembles the baseline artificial observation with a change from $lngSegm = 0$ to $lngSegm = 1$, indicating that the wayfinder is walking on a long segment. In all of these three cases, the time that the wayfinder would ask for instructions decreases. As it can be seen, the most influential explanatory variables appear to be length of segment (*lngSegm*) along with the below average degree of openness (*BFI_o_low*).

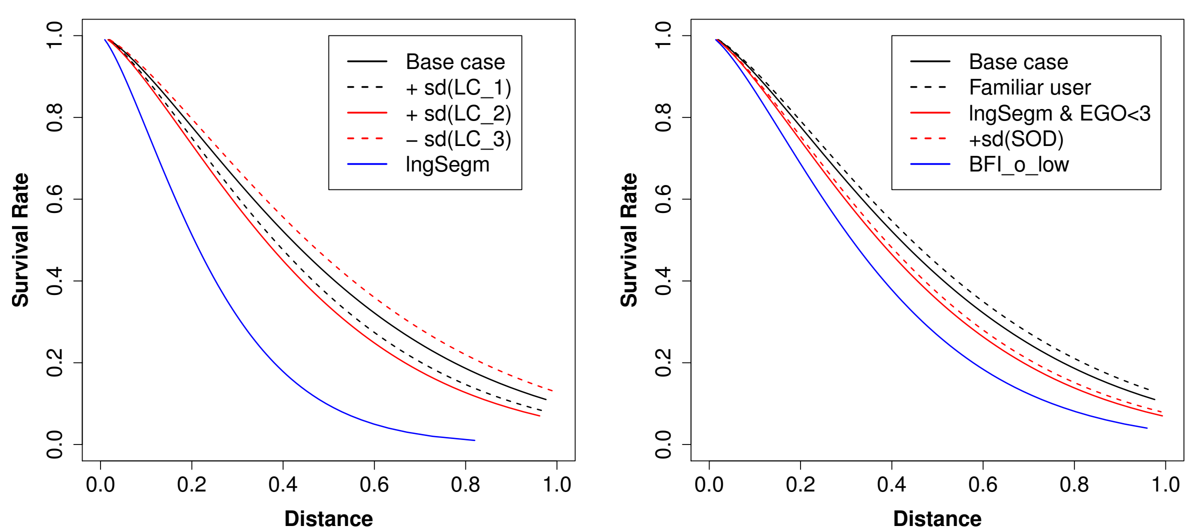

Figure 5: Variation of survival rate predictions due to explanatory variables modifications. The corresponding modifications are applied to a base case scenario in the following manner: continuous variables=± 1 standard deviation, dummy variables=1.

6 Discussion

Given the data-specific nature of survival analysis, we are only able to make assumptions about why the given variables are influential. We will, therefore, present possible reasons and state complementary open research questions which can be derived from our results. We will discuss these results by group of variables, i.e., we will start with the group of environmental variables (*LC_**), continue with personal variables (*age_gt_40* and *BFI_o_low*) and, finally, discuss the interactions among orientation and person/route related variables (*SOD:familiar*, *SOD:unfamiliar*, *EGO_lt_three:lngSegm*) as well as the interaction between familiarity and segment length (*unfamiliar:lngSegm*).

6.1 Environmental variables

According to our model, people request route instructions the earlier for route segments the higher the proportion of land cover classes *LC_1* or *LC_2* is along them. *LC_1* represents the Urban Atlas (European Comission, 2012) class *12100 (Industrial, commercial, public, military and private units)*, whereas, *LC_2* subsumes Urban Atlas classes 11100 and 11210, (European Comission, 2012, p. 9), i.e., it comprises areas of predominantly residential use with a soil sealing of >50%. Both variables show a considerable difference in average area of building footprints (*LC_1:* 1816.73m^2, *LC_2:* 661.55m^2). In urban areas, *LC_1* covers mostly public buildings (e.g., universities, museums) and associated features. *LC_2* shows a medium-sized positive correlation (Spearman's $\rho = 0.56$) with the presence of OSM features tagged as *shop*. However, the density of built-up areas, which we calculated based on OSM building footprints and the extent of landcover class polygons along the route segments is very similar (*LC_1*: 46%; *LC_2*: 50%). This result and the fact that both variables show a negative impact on timing (i.e., the higher the value for *LC_1* and *LC_2* the earlier people would ask for instructions) suggests that the impact of *LC_1* and *LC_2* may stem from similar source. One possible source is a limited line of sight in these environments. For example, crowds in public places are likely to occur in areas with many public buildings or shops. In addition to that, the high density of built-up areas may cause a limited line of sight on upcoming intersections in general. This interpretation is in line with, e.g., research indicating the importance of visibility in advance for landmark salience (see, e.g., Kattenbeck, 2017; Winter, 2003). The interpretation also resembles the idea of on visibility index, which was, according to (Farr, Kleinschmidt, Yarlagadda, & Mengersen, 2012), introduced by Braaksma and Cook (1980). This index is based on the number of direct sight lines when moving towards a target (e.g., an intersection) and can be used as a direct measure of ease of wayfinding. Therefore, a wayfinder might need an instruction earlier in an occluded environment to make the wayfinding task easier as this allows the person to recognize the landmark of the upcoming turn earlier. Another explanation for the negative impact of the variables *LC_1* and *LC_2* could be that due to the perceived complexity of the environment which may be caused by the building density, wayfinders plan ahead in order to gain enough time to make the spatial decision and identify the object of interest among the possible plethora of landmarks.

6.2 Personal variables

With respect to personal variables, our results suggest that participants older than 40 years of age tend to request route instructions later, a finding based on approx. 10% of all route segments. All of these participants have not only spent the largest fraction of their adulthood in Vienna but also considered their ability to find their way around in Vienna nearly all above average ($M = 71.1$, $min_{age>40} = 71$, $max_{age>40} = 100$). Therefore, it is reasonable to assume that the cognitive map(Tolman, 1948) or cognitive graphs (see Warren, 2019) of this group of people is well developed and, hence, had an impact on requesting a route instruction later as these mental representations develop over time based on experience (see, e.g., Kitchin, 1994): These persons are experienced wayfinders in this particular urban environment and, hence, they feel less pressure to reduce their uncertainty by requesting a route instruction early on. At the same time, our participants do not belong to an age group ($max_{age} = 59$) for which empirical evidence suggest that spatial abilities deteriorate (see, e.g., Head & Isom, 2010, who tested people with a mean age of 71 years). Our findings on age, however, are different to those reported in Giannopoulos et al. (2017), who found a main effect for both, age and the age group of people who are older than 27 years of age. Hence, further investigation of potential reasons for the difference found is one of the research questions opened up by the findings of the current study. A second finding with respect to personal variables relates to the participants' personality traits: People having a below average degree of openness (measured by the BFI-10 scale and according to norm data given in Rammstedt et al., 2013) request a route instruction earlier. Scholars tend to agree that human personality can be described along five dimensions (see John & Srivastava, 1999, for an overview on the history of these concepts), which are often referred to as *Big Five* (Goldberg, 1990): *extraversion*, *openness* to experience (also known as open-mindedness), *agreeableness*, *conscientiousness* and *emotional stability/neuroticism*. According to (Costa & McCrae, 2010), people who score high on trait *openness* "[. . .] enjoy novelty and variety [. . . and] have a high appreciation of beauty in art and nature" (Costa & McCrae, 2010, p. 243). The city of Vienna is, generally speaking, a city with a lot of historic buildings, with highly decorated facades. People having a low level of openness may, therefore, pay less attention to the beauty of this environment and ask for an instruction early on in order to have more time to focus on the wayfinding task itself.

6.3 Interactions between variables

Drawing on common sense, a main effect of familiarity on timing seems plausible, i.e., we would have expected that people ask later for instructions when traveling on familiar routes (and vice versa). However, familiarity is only rendered significant as an interaction term: When walking through unfamiliar areas, persons request route instructions earlier on those segments which are longer than $120m$. One potential explanation would be that the upcoming decision point is visible later on longer segments, for example due to a higher number of occluding objects on these segments. As a consequence, unfamiliar persons experience a higher degree of difficulty of wayfinding (Farr et al., 2012) and, hence, uncertainty due to their lack of a cognitive map/graph.

When interpreting the meaning/influence of the interactions relating to spatial orientation, one needs to keep in mind how these values are calculated. We used the German language self-report scale on spatial strategies developed by Münzer and Hölscher (2011). In analyzing this data, we follow the advice given in Kattenbeck and Kreuzpointner (n.d.): They provide evidence for the fact that a bifactor model for the scale fits a representative sample ($N = 4037$) of the German population better than the three-factor correlational model (involving the subfactors egocentric/global orientation (EGO), allocentric orientation and cardinal direction strategies) suggested by Münzer, Fehringer, and Kühl (2016). Kattenbeck and Kreuzpointner extract Sense of Direction (SOD) as a general factor from the data and provide evidence that the three subfactors remain significant. In their bifactor model, EGO can be interpreted as a person's preference for egocentric orientation. The obtained factor scores are standardized, i.e., zero represents an average self-report value. It is important to note, that in our sample all participants score above average (positive sign) on all four (sub-)factors.

Our results suggest that there is a subgroup of people among the group of people who prefer egocentric orientation more than average: People scoring below three on the egocentric factor request route instructions on long segments ($>120m$) later. As the direction of this effect is counter-intuitive, further investigations in controlled settings are required to assess whether this effect holds across samples and what it actually means (see section 7).

Finally, the interaction terms suggest that the level of familiarity affects the timing of route instruction requests even for wayfinders with a high sense of direction: The higher the SOD of participants, the earlier they request the route instruction across conditions. However, for the unfamiliar condition, the route instruction is requested 20% earlier than in the familiar condition. This change aligns with the common sense expectation although it is dependent on a persons SOD. This effect, however, is contradicting the finding by Giannopoulos et al. (2017), who report a delaying effect by SOD on route instruction requests. This raises, on the one hand, questions about ecological validity of controlled lab study results. On the other hand, it imposes questions about differences in self-report measurement of SOD, as Giannopoulos et al. (2017) base their results on the Santa Barbara Sense of Direction scale (Hegarty et al., 2002).

6.4 Limitations

Three limitations apply to our study, two of which relate to generalizability. First, our sample of participants includes only people who rate their sense of direction and spatial strategies above average (e.g., $min_{SOD} = 1.9$, $M_{SOD} = 4.8$). Hence, it remains unknown whether persons who are less well-oriented would have acted differently. Second, and similarly, the age distribution of our participants is heavily right-skewed. A final limitation deals with human behavior: Due to the nature of the survival analysis, we had to exclude participants who have chosen to request a route instruction right at the beginning of a segment. In order to understand this behavior we would have needed to collect the reasons for clicks, which we decided not to do in the current study in order to avoid confounding effects.

7 Conclusion and Future Work

While many research efforts on reducing cognitive load in wayfinders by means of wayfinding assistance systems exist, timing of route instructions has been almost neglected so far. Using Giannopoulos et al. (2017) as a starting point, we conducted a within-subject, in-situ wayfinding study suitable to model preferred timing of pedestrian navigation instructions by means of survival analysis. In doing so, we were able to gain an insight into when a wayfinding assistance system should automatically present a route instruction. We applied an AFT model based on a Weibull distribution to identify which environmental, personal, trial or route related variables have an impact on timing requests and find that variables of each of these levels are influential. Given the model-driven approach we discussed possible reasons for their influence and highlight inconsistencies between our model and the timing model obtained by Giannopoulos et al. (2017). Based on the results and the discussion thereof, at least three main areas of research questions arise:

Spatial orientation At least, three strands of open questions can be identified based on our results on the impact of SOD. The first strand relates to disentangling the impact of SOD stratified by familiarity, in particular for below average wayfinders. Second, potential impacts of using different self-report surveys to measure SOD on timing should be investigated. Thirdly, it remains an open research question whether different levels of egocentric preference yield an impact on timing across samples.

Motivation While we have focused on collecting behavioral correlates, one of the core questions which arise is on the motivations of a person to request a navigation instruction at a specific point in time, its relation to spatial strategies and the degree of uncertainty in wayfinding as perceived by participants. Based on our results, the experimental protocol used to study this problem should include a variety of land covers along routes, spatial layouts, occluding objects (e.g., cars) along a route and different levels of decision point visibility. Devising a protocol which is suitable for both, in-situ and virtual environment settings may be particular important in this case in order to gain also ecological validity insights.

Age The influence of *age_gt_40* in the present model could have a different source than the effect found in Giannopoulos et al. (2017), as participants who belong to the age group *age_gt_40* in the current study have spent a majority of their life time in Vienna, whereas all participants in their study were unfamiliar with the artificial city. It would be worthwhile to investigate how persons who have lived most of their life in Vienna and persons of similar age who have not or have even spent most of their life in non-urban environments differ in terms of timing preferences. This would also allow to investigate differences in spatial strategies employed between these two groups.

References

Anastasopoulos, P. C., Islam, M. B., Perperidou, D., & Karlaftis, M. G. (2012). Hazard-based analysis of travel distance in urban environments: longitudinal data approach. *Journal of Urban Planning and Development*, *138*(1), 53–61.

Barhorst-Cates, E. M., Rand, K. M., & Creem-Regehr, S. H. (2019). Navigating with peripheral field loss in a museum: learning impairments due to environmental complexity. *Cognitive Research: Principles and Implications*, *4*, 41. doi: 10.1186/s41235-019-0189-9

Bhat, C. R., & Pinjari, A. R. (2007). Duration modeling. In *Handbook of Transport Modelling: 2nd Edition* (pp. 105–131). Emerald Group Publishing Limited.

Bienk, S., Kattenbeck, M., Ludwig, B., Müller, M., & Ohm, C. (2013). I want to view it my way - interfaces to mobile maps should adapt to the user's orientation skills. In *Proceedings of the 12th International Conference on Mobile and Ubiquitous Multimedia, MUM 2013.* doi: 10.1145/2541831.2541841

Boeing, G. (2017, 4). Osmnx: A python package to work with graph-theoretic openstreetmap street networks. *The Journal of Open Source Software*, *2*, 215. doi: 10.21105/joss.00215

Braaksma, J. P., & Cook, W. J. (1980). Human orientation in transportation terminals. *Transportation Engineering Journal of the American Society of Civil Engineers*, *106*(2), 189–203.

Brunyé, T. T., Gardony, A. L., Holmes, A., & Taylor, H. A. (2018). Spatial decision dynamics during wayfinding: intersections prompt the decision-making process. *Cognitive Research: Principles and Implications*, *3*. doi: 10.1186/s41235-018-0098-3

Brügger, A., Richter, K.-F., & Fabrikant, S. I. (2018). Which egocentric direction suffers from visual attention during aided wayfinding? In *Eye Tracking for Spatial Research, Proceedings of the 3rd International Workshop.* doi: https://doi.org/10.3929/ethz-b-000222472

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

Caduff, D., & Timpf, S. (2008). On the assessment of landmark salience for human navigation. *Cognitive Processing*, *9*(4), 249–267.

Cheraghi, S. A., Almadan, A., & Namboodiri, V. (2019, oct). CityGuide: A Seamless Indoor-Outdoor Wayfinding System for People With Vision Impairments. In *The 21st international acm sigaccess conference on computers and accessibility* (pp. 542–544). New York, NY, USA: ACM. doi: 10.1145/3308561.3354621

Coors, V., Elting, C., Kray, C., & Laakso, K. (2005). Presenting route instructions on mobile devices: From textual directions to 3d visualization. *Exploring Geovisualization*, 529-550. doi: 10.1016/B978-008044531-1/50445-0

Core Team, R., et al. (2013). *R: A language and environment for statistical computing.* Vienna, Austria.

Costa, P. T., & McCrae, R. R. (2010). The NEO Inventories. In *Neo PI-R professional manual0* (pp. 223–256). American Psychological Association.

Ding, D., Parmanto, B., Karimi, H. A., Roongpiboonsopit, D., Pramana, G., Conahan, T., & Kasemsuppakorn, P. (2007). Design considerations for a personalized wheelchair navigation system. In *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (p. 4790-4793). doi: 10.1109/IEMBS.2007.4353411

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

European Comission. (2012). *Mapping guide for a european urban atlas — copernicus.* Retrieved from https://land.copernicus.eu/user-corner/technical-library/urban-atlas-mapping-guide (last accessed November 30, 2020)

Fang, Z., Li, Q., & Shaw, S. L. (2015). What about people in pedestrian navigation? *Geo-Spatial Information Science*, *18*, 135-150. doi: 10.1080/10095020.2015.1126071

Farr, A. C., Kleinschmidt, T., Yarlagadda, P., & Mengersen, K. (2012). Wayfinding: A simple concept, a complex process. *Transport Reviews*, *32*, 715-743. doi: 10.1080/01441647.2012.712555

Geldof, S., & Dale, R. (n.d.). Improving route directions on mobile devices. In *ISCA Tutorial and Research Workshop (ITRW) on Multi-Modal Dialogue in Mobile Environments.* Retrieved from http://science.mq.edu.au/~rdale/publications/papers/2002/final42.pdf

Giannopoulos, I., Jonietz, D., Raubal, M., Sarlas, G., & Stähli, L. (2017). Timing of Pedestrian Navigation Instructions. In E. Clementini, M. Donnelly, M. Yuan, C. Kray, P. Fogliaroni, & A. Ballatore (Eds.), *13th International Conference on Spatial Information Theory (COSIT 2017)* (Vol. 86, pp. 16:1–16:13). Dagstuhl, Germany: Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik. doi: 10.4230/LIPIcs.COSIT.2017.16

Giannopoulos, I., Kiefer, P., & Raubal, M. (2015). Gaze nav: Gaze-based pedestrian navigation. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services* (p. 337-346). Association for Computing Machinery, Inc. doi: 10.1145/2785830.2785873

Giannopoulos, I., Kiefer, P., Raubal, M., Richter, K.-F., & Thrash, T. (2014). Wayfinding Decision Situations: A Conceptual Model and Evaluation. In *Proceedings of the 8th International Conference on Geographic Information Science (GIScience 2014)* (pp. 221–234). doi: 10.1007/978-3-319-11593-1_15

Goldberg, L. R. (1990). An alternative "description of personality": The Big-Five factor structure. *Journal of Personality and Social Psychology,*, *59*, 1216–1229.

Google Inc. (2020). *Google text-to-speech documentation.* Retrieved from https://cloud.google.com/text-to-speech/docs (accessed November 30, 2020)

Götze, J., & Boye, J. (2016). Learning landmark salience models from users' route instructions. *Journal of Location Based Services*, *10*, 47-63. doi: 10.1080/17489725.2016.1172739

Hazzard, A., Benford, S., & Burnett, G. (2014). Walk this way: Musically guided walking experiences. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (p. 605-614). Association for Computing Machinery. doi: 10.1145/2556288.2557250

Head, D., & Isom, M. (2010, 5). Age effects on wayfinding and route learning skills. *Behavioural Brain Research*, *209*, 49-58. doi: 10.1016/j.bbr.2010.01.012

Hegarty, M., Richardson, A. E., Montello, D. R., Lovelace, K., & Subbiah, I. (2002). Development of a self-report measure of environmental spatial ability. *Intelligence*, *30*, 425-447.

Hirtle, S., Richter, K.-F., Srinivas, S., & Firth, R. (2010). This is the tricky part: When directions become difficult. *Journal of Spatial Information Science*(1), 53–73. doi: 10.5311/JOSIS.2010.1.5

Holland, S., Morse, D. R., & Gedenryd, H. (2002). AudioGPS: Spatial Audio Navigation with a Minimal Attention Interface. *Personal and Ubiquitous Computing*, *6*, 253–259. doi: 10.1007/s007790200025

Hosmer Jr, D. W., Lemeshow, S., & May, S. (2011). *Applied survival analysis: regression modeling of time-to-event data*. John Wiley & Sons.

Hölscher, C., Tenbrink, T., & Wiener, J. M. (2011). Would you follow your own route description? cognitive strategies in urban route planning. *Cognition*, *121*, 228-247. doi: 10.1016/j.cognition.2011.06.005

Ishikawa, T. (2019). Satellite navigation and geospatial awareness: Long-term effects of using navigation tools on wayfinding and spatial orientation. *Professional Geographer*, *71*. doi: 10.1080/00330124.2018.1479970

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In L. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (pp. 102–138). New York: Guilford Press.

Kalbfleisch, J. D., & Prentice, R. L. (2011). *The statistical analysis of failure time data* (Vol. 360). John Wiley & Sons.

Kattenbeck, M. (2017). How subdimensions of salience influence each other. comparing models based on empirical data. In *Proceedings of the 13th International Conference on Spatial Information Theory (COSIT 2017)* (Vol. 86, pp. 1–10). doi: 10.4230/LIPIcs.COSIT.2017.10

Kattenbeck, M., & Kreuzpointner, L. (n.d.). Sense of Direction and Spatial Strategies. A Bifactor Structure for the Spatial Strategies Questionnaire Fragebogen Räumliche Strategien. *PLoS One*. (in revision)

Kattenbeck, M., Nuhn, E., & Timpf, S. (2018). Is salience robust? A heterogeneity analysis of survey ratings. In *10th International Conference on Geographic Information Science (GIScience 2018)* (Vol. 114, p. 1-7). doi: 10.4230/LIPIcs.GIScience.2018.7

Kitchin, R. (1994). Spatial familiarity as a variable in cognitive mapping. *Swansea Geographer*, *31*, 42-52.

Klippel, A., Richter, K. F., & Hansen, S. (2009). Cognitively ergonomic route directions. *Handbook of Research on Geoinformatics*, 230–238. doi: 10.4018/978-1-59140-995-3.ch029

Klippel, A., Tappe, H., & Habel, C. (2002). Pictorial representations of routes: Chunking route segments during comprehension. In *International Conference on Spatial Cognition* (pp. 11–33).

Krukar, J., Anacta, V. J., & Schwering, A. (2020). The effect of orientation instructions on the recall and reuse of route and survey elements in wayfinding descriptions. *Journal of Environmental Psychology*, *68*, 101407. doi: 10.1016/j.jenvp.2020.101407

Lander, C., Herbig, N., Löchtefeld, M., Wiehr, F., & Krüger, A. (2017). Inferring landmarks for pedestrian navigation from mobile eye-tracking data and google street view. *Conference on Human Factors in Computing Systems - Proceedings*, *Part F1276*, 2721-2729. doi: 10.1145/3027063.3053201

Lazem, S. Y., & Sheta, W. M. (2005). Automatic Landmark Identification in Large Virtual Environment: A Spatial Data Mining Approach. In *Proceedings of the Ninth International Conference on Information Visualisation (IV'05)* (p. 752-757). IEEE Computer Society.

Lovelace, K. L., Hegarty, M., & Montello, D. R. (1999). Elements of good route directions in familiar and unfamiliar environments. *Spatial Information Theory: Cognitive and Computational Foundations of Geographic Information Science*, 65-82.

May, A. J., Ross, T., Bayer, S. H., & Tarkiainen, M. J. (2003). Pedestrian navigation aids: information requirements and design implications. *Personal and Ubiquitous Computing*, *7*, 331-338.

Mazurkiewicz, B., Kattenbeck, M., Kiefer, P., & Giannopoulos, I. (2020). Not Arbitrary, Systematic! Average-Based Route Selection for Navigation Experiments. In K. Janowicz & J. A. Verstegen (Eds.), *11th International Conference on Geographic Information Science (GIScience 2021) - Part I* (Vol. 177, pp. 8:1–8:16). Dagstuhl, Germany: Schloss Dagstuhl–Leibniz-Zentrum für Informatik. doi: 10.4230/LIPIcs.GIScience.2021.I.8

Michon, P.-E., & Denis, M. (2001). When and why are visual landmarks used in giving directions? In *International Conference on Spatial Information Theory (COSIT 2001)* (pp. 292–305).

Millonig, A., & Schechtner, K. (2007, 3). Developing landmark-based pedestrian-navigation systems. *IEEE Transactions on Intelligent Transportation Systems*, *8*, 43-49. doi: 10.1109/TITS.2006.889439

Montello, D. R. (2005). Navigation. In *The Cambridge Hanbook of Visuospatial Thinking* (p. 257-294). Cambridge University Press.

Münzer, S., Fehringer, B. C., & Kühl, T. (2016). Validation of a 3-factor structure of spatial strategies and relations to possession and usage of navigational aids. *Journal of Environmental Psychology*, *47*. doi: 10.1016/j.jenvp.2016.04.017

Münzer, S., & Hölscher, C. (2011). Entwicklung und Validierung eines Fragebogens zu räumlichen Strategien. *Diagnostica*, *57*(3), 111–125.

Nothegger, C., Winter, S., & Raubal, M. (2004). Selection of salient features for route directions. *Spatial Cognition & Computation*, *4*, 113-136.

Nuhn, E., & Timpf, S. (2017). A multidimensional model for selecting personalised landmarks. *Journal of Location Based Services*, *11*, 153-180. doi: 10.1080/17489725.2017.1401129

Nuhn, E., & Timpf, S. (2020). How to Model (Personalised) Landmarks ? In J. Šķilters, N. Newcombe, & D. Uttal (Eds.), *Spatial Cognition XII. Spatial Cognition 2020* (p. 33-49).

Springer International Publishing. doi: 10.1007/978-3-030-57983-8

Quesnot, T., & Roche, S. (2015). Quantifying the Significance of Semantic Landmarks in Familiar and Unfamiliar Environments. In S. I. Fabrikant, M. Raubal, M. Bertolotto, C. Davies, S. Freundschuh, & S. Bell (Eds.), *Proceedings of the international conference on spatial information theory* (Vol. 9368, p. 468-489). Springer International Publishing.

Rammstedt, B., Kemper, C. J., & Céline, M. (2013). Eine kurze Skala zur Messung der fünf Dimensionen der Persönlichkeit A Short Scale for Assessing the Big Five Dimensions of Personality. *Methoden, Daten, Analyse*, *7*(2), 233–249. doi: 10.12758/mda.2013.013

Rammstedt, B., Kemper, C. J., Klein, M. C., Beierlein, C., & Kovaleva, A. (2012). Eine kurze Skala zur Messung der fünf Dimensionen der Persönlichkeit. *GESIS-Working Papers*, *22*(2), 1–32. Retrieved from http://pub.uni-bielefeld.de/publication/2575688

Raubal, M., & Winter, S. (2002). Enriching wayfinding instructions with local landmarks. In M. Egenhofer & D. Mark (Eds.), *International conference on geographic information science* (p. 243-259). Springer.

Rehrl, K., Häusler, E., Leitinger, S., & Bell, D. (2014). Pedestrian navigation with augmented reality, voice and digital map: final results from an in situ field study assessing performance and user experience. *Journal of Location Based Services*, *8*(2), 75–96.

Richter, K.-F., & Klippel, A. (2005). A Model for Context-Specific Route Directions. In C. Freksa, M. Knauff, B. Krieg-Brückner, B. Nebel, & T. Barkowsky (Eds.), *Spatial Cognition IV. Reasoning, Action, Interaction. Spatial Cognition 2004* (p. 58-78). doi: 10.1007/978-3-540-32255-9_4

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

Ross, T., May, A., & Thompson, S. (2004). The Use of Landmarks in Pedestrian Navigation Instructions and the Effects of Context. In *International Conference on Mobile Human-Computer Interaction Mobile HCI 2004* (p. 300-304). doi: 10.1007/978-3-540-28637-0_26

Rousell, A., & Zipf, A. (2017). Towards a landmark-based pedestrian navigation service using OSM data. *ISPRS International Journal of Geo-Information*, *6*(3). doi: 10.3390/ijgi6030064

Sarjakoski, T., Kettunen, P., Halkosaari, H.-M., Laakso, M., Rönneberg, M., Stigmar, H., & Sarjakoski, T. (2013). Landmarks and a Hiking Ontology to Support Wayfinding in a National Park During Different Seasons. In M. Raubal, D. M. Mark, & A. U. Frank (Eds.), *Cognitive and Linguistic Aspects of Geographic Space. New Perspectives on Geographic Information Research.* Heidelberg et al.: Springer.

Sarlas, G., & Axhausen, K. W. (2018). Commuting distance and individual accessibility. *Arbeitsberichte Verkehrs-und Raumplanung, IVT, ETH Zurich*, *1376*.

Schmidt, A., Beigl, M., & Gellersen, H.-W. (1999). There is more to context than location. *Computers & Graphics*, *23*, 901.

Schwering, A., Krukar, J., Li, R., Anacta, V. J., & Fuest, S. (2017). Wayfinding through orientation. *Spatial Cognition and Computation*, *17*, 273-303. doi: 10.1080/13875868.2017.1322597

Stern, E., & Portugali, J. (1999). Environmental cognition and decision making in urban navigation. *Wayfinding behavior: Cognitive mapping and other spatial processes*, 99-119.

Story, R. (2013). *Folium.* Retrieved from https://python-visualization.github.io/folium/ (accessed November 30, 2020)

Stähli, L., Giannopoulos, I., & Raubal, M. (2020). Evaluation of pedestrian navigation in smart cities. *Environment and Planning B: Urban Analytics and City Science*, 1-18. doi: 10.1177/2399808320949538

Therneau, T. (2014). A package for survival analysis in S. R package version 2.37-4.

Tolman, E. C. (1948). Cognitive Maps in Rats and Men. *Psychological Review*, *55*(4), 189–208.

Tom, A., & Denis, M. (2004). Language and spatial cognition: comparing the roles of landmarks and street names in route instructions. *Applied Cognitive Psychology*, *18*(9), 1213-1230. doi: https://doi.org/10.1002/acp.1045

Völkel, T., & Weber, G. (2008). Routecheckr: personalized multicriteria routing for mobility impaired pedestrians. In *Proceedings of the 10th international ACM SIGACCESS conference on Computers and accessibility* (pp. 185–192).

Waldorf, B. (2003). Spatial patterns and processes in a longitudinal framework. *International Regional Science Review*, *26*(3), 269–288.

Walther-Franks, B., & Malaka, R. (2008). Evaluation of an augmented photograph-based pedestrian navigation system. In A. Butz, B. Fisher, A. Krüger, P. Olivier, & M. Christie (Eds.), *Smart Graphics* (pp. 94–105). Berlin, Heidelberg: Springer Berlin Heidelberg.

Wang, J., & Ishikawa, T. (2018). A system of automatic generation of landmark-based pedestrian navigation instructions and its effectiveness for wayfinding. In *German Conference on Spatial Cognition* (pp. 326–340).

Warren, W. H. (2019, 2). Non-euclidean navigation. *The Journal of Experimental Biology*, *222*, 1-10. doi: 10.1242/jeb.187971

Winter, S. (2003). Route adaptive selection of salient features. In *International conference on spatial information theory* (pp. 349–361).

Zimmer, H. D., Münzer, S., & Baus, J. (2010). From resource-adaptive navigation assistance to augmented cognition. In *Resource-Adaptive Cognitive Processes* (pp. 35–53). Springer.