Informed Route Selection for Experimental Design and the Potential of Free Choices for Spatial Knowledge Acquisition

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Bartosz Mazurkiewicz, MSc
Matrikelnummer 11914271

an der Fakultät für Mathematik und Geoinformation
der Technischen Universität Wien

Betreuung: Univ.Prof. Dr.sc. Ioannis Giannopoulos

Diese Dissertation haben begutachtet:

Kai-Florian Richter

Christian Kray

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Bartosz Mazurkiewicz

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Bartosz Mazurkiewicz, MSc

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Kurzfassung

Navigationssysteme begleiten uns täglich und viele Menschen nutzen sie sowohl in bekannten als auch in unbekannten Umgebungen. Üblicherweise geben diese Navigationssysteme dem Benutzer die kürzeste Route vor. Obwohl dieser Ansatz in bestimmten Situationen vorteilhaft sein kann, folgt der Benutzer dabei den Anweisungen passiv. Das wiederum schränkt die Interaktion mit der Umgebung und selbstständige Entscheidungen ein. Des Weiteren gibt es Literatur, die darauf hindeutet, dass die Nutzung von Navigationssystemen unsere räumliche Wahrnehmung und Orientierung negativ beeinflussen kann. Als häufiger Grund dafür wird geteilte Aufmerksamkeit genannt, da der Nutzer sich abwechselnd auf das Navigationssystem und die Umgebung konzentrieren muss. In den letzten Jahren wurden mehrere Navigationsansätze vorgeschlagen, um diese Auswirkungen abzuschwächen und den Erwerb von räumlichem Wissen (auf Englisch *spatial knowledge acquisition*) zu unterstützen. Diese Ansätze versuchen, den Benutzer aktiv in den Entscheidungsprozess einzubinden. Allerdings geben diese Systeme immer noch eine vordefinierte Route vor und fordern weiterhin eine geteilte Aufmerksamkeit. Dabei werden die räumlichen Fähigkeiten des Benutzers meistens nicht berücksichtigt. Dies steht im Gegensatz zu dieser Arbeit, in der die Berücksichtigung von räumlichen Benutzerfähigkeiten eine personalisierte Unterstützung erlaubt. In dieser Arbeit werden zwei neue Navigationskonzepte vorgestellt, die die oben genannten Probleme berücksichtigen, indem sie dem Benutzer eine aktive Rolle im Entscheidungsprozess zuschreiben. Das erste Konzept heißt *Free Choice Navigation* (FCN) und ist ein nicht visueller Navigationsansatz, der einen Kompromiss zwischen freier Erkundung der Umgebung, der Anzahl an Navigationsanweisungen und einer maximalen Routenlänge eingeht. Anhand von geschätzten Wahrscheinlichkeiten und den räumlichen Fähigkeiten des Benutzers versucht dieser Navigationsansatz zu bestimmen, ob der Benutzer an der nächsten Kreuzung Unterstützung benötigt. Der zweite vorgestellte Navigationsansatz heißt *Beeline Augmented Reality* (BeeAR) und zeigt das Ziel permanent mittels einer Augmented-Reality-Datenbrille an. Dadurch kompensiert er den potenziellen Fehler, der bei dem FCN-Ansatz durch die Schätzung der Benutzerorientierung entstehen kann. In beiden Ansätzen soll die erhaltene Informationsmenge reduziert werden und der Nutzer aktiv am Entscheidungsprozess teilnehmen. Daher wird erwartet, dass diese Ansätze den Erwerb von räumlichem Wissen unterstützen. In einer empirischen Nutzerstudie wurden diese zwei neuen Konzepte evaluiert. Dabei diente der weitverbreitete Turn-by-Turn-Navigationsansatz als Vergleichsgrundlage. Eine der wichtigsten Entscheidungen bei der Planung von solchen

Experimenten ist die Auswahl der Route(n) innerhalb eines Testgebiets. Diese müssen experimentspezifische Kriterien erfüllen. Nach jetzigem Stand gibt es kaum systematische Informationen über den möglichen Einfluss von Routen auf Studienergebnisse. Daher wird in einer agentenbasierten Simulationsstudie der mögliche Einfluss der Routenauswahl auf die Studienergebnisse untersucht. Außerdem wird untersucht, ob sich die Stichprobengröße auf diesen potenziellen Einfluss auswirkt. Der zweite Beitrag dieser Arbeit zur Bedeutung der Routenauswahl in Navigationsexperimenten ist die Entwicklung eines Frameworks für systematische und reproduzierbare Routenauswahl in Navigationsexperimenten. In Anbetracht der Vielzahl möglicher Routen und ihrer potenziellen Auswirkungen auf die Studienergebnisse sollte dieses Framework die ökologische Validität erhöhen, da die ausgewählten Routen die experimentspezifischen Kriterien am besten erfüllen. Das wiederum ermöglicht eine größtmögliche Verallgemeinerung der Ergebnisse. Neben der Auswahl von Routen aus einer potenziellen Routengrundgesamtheit ermöglicht das Framework die Suche von ähnlichen Routen in verschiedenen geografischen Gebieten. Diese Art der Unterstützung erleichtert die Studienreplikation in anderen Ländern. Darüber hinaus wird ein Verfahren zur Ermittlung von Routen vorgeschlagen, die wahrscheinlich zu Ergebnissen führen, die mit den meisten Routen im Testgebiet übereinstimmen.

Abstract

Navigation assistance systems have become widespread, and many people use them daily in familiar or unfamiliar areas. These navigation systems require the user to follow a predefined route, usually the shortest one. Although this approach can be beneficial in certain situations, this circumstance reduces the user to a passive follower, limiting at the same time the interaction with the environment and active decisions. Furthermore, the literature suggests that the usage of navigation assistance systems may adversely affect spatial cognition and orientation, often explained by the forced attention shifts between the supporting navigation system and the environment. Several approaches focusing on enhancing spatial knowledge acquisition have been proposed over the years to mitigate these effects. These approaches try to engage the user in the decision-making process actively. However, they still force users to divide attention or follow a predefined route. In contrast to this work, they do not incorporate the user's environmental spatial abilities allowing for personalized assistance. The work presents two novel concepts tackling these problems by increasing the user's active participation in the decision-making process. The first concept, *Free Choice Navigation* (FCN), is a non-visual navigation approach focusing on a compromise between free exploration, the number of issued instructions, and a maximum allowed walking distance. Based on estimated probabilities and environmental spatial abilities, this approach also tries to determine whether the user needs assistance at the next junction. The second introduced navigation approach, *Beeline Augmented Reality* (BeeAR), is permanently displaying the destination through augmented reality data glasses, compensating for the potential errors in users' orientation estimation of the FCN approach. Both approaches focus on decreasing the amount of information provided to the user and involve the user in the decision-making process. Therefore, these approaches are expected to support spatial knowledge acquisition. Both novel concepts were evaluated through an in situ empirical user study using the state-of-the-art turn-by-turn approach as a baseline. One of the most crucial experimental design decisions for such evaluations is selecting the route(s) within an experimental area that must satisfy experiment-specific criteria. As of today, there is little systematic information about the potential influence of routes on study results. Therefore, an agent-based simulation study demonstrates the potential influence of route selection on study results. Furthermore, it will be scrutinized if the sample size impacts this potential influence. The second contribution of this work regarding the importance of route selection in navigation experiments is the development of a route

selection framework for wayfinding experiments allowing for systematic and reproducible route selection. Given the abundance of possible routes and their potential impact on study results, this framework should increase ecological validity as the selected routes best satisfy the experiment-specific criteria, which in turn allows for generalizing the findings as much as possible. Besides selecting routes from a potential route population, the framework enables finding similar routes in different geographic areas, which facilitates study replication in other countries. Moreover, a procedure for finding routes leading likely to results in line with most routes in the experimental area is proposed.

Contents

CHAPTER 1

Introduction

In this work, two main aspects are addressed: (1) the potential of giving the user more decision-making options while using a pedestrian navigation assistance system and the impact thereof on spatial knowledge acquisition; (2) the potential impact of route selection in wayfinding experiments and a systematic approach for route selection.

1.1 Motivation and Problem Statement

The motivation and the problems addressed in this thesis will be illustrated with two scenarios, one from everyday life and one from academia.

Two friends, Alice and Bob, are walking down the street in the city center. After a stroll of roughly 30 minutes, they got hungry. Bob remembers that he recently passed by a newly opened Polish restaurant in the city center and wrote down its name on his smartphone. He became only aware of the restaurant because the noise of the last refinements drew his attention. Unfortunately, his smartphone runs out of battery, but he remembers the first part of the restaurant's name. Alice takes out her smartphone and starts typing. Both are convinced that they will know the exact location within seconds and receive navigation instructions to the restaurant. To their surprise, the restaurant is not listed in the result. None of them knows that the restaurant's information has yet to be included in any of the main map provider services. Alice asks Bob if he remembers the rough location or any other details of the environment close to the restaurant. Bob admits that he was very much focused on the navigation instructions he received from the smartphone and that only by chance the noise made him aware of the restaurant. He does not remember any further details of the environment he traversed back then. If he had interacted more with the environment, Bob could potentially recall further elements of the environment that are findable on a map.

This short scenario illustrates one type of navigation system users (Webber et al., 2012), an inattentive user, following the navigation instructions and a predefined route passively without paying attention to the environment. Missing potentially valuable information may have different degrees of severity. It can vary from knowing where the next defibrillator is in an emergency to being aware of the next Colombian restaurant with a group of friends visiting you. Not every information is to be found easily on the internet. The information may be missing or outdated (e.g., Camboim et al., 2015; Deitz et al., 2021; Weiss et al., 2020). Therefore, it is important to know our surroundings. Missing information from the environment is one of the negative effects these navigation systems may have, as the literature suggests that the usage of navigation assistance systems may adversely affect spatial cognition and orientation (e.g., Fenech et al., 2010; Ishikawa, 2019; Dahmani and Bohbot, 2020). This negative impact is often explained by users needing to divide their attention between the supporting navigation system and the environment (e.g., Gardony et al., 2013). The negative impact on spatial cognition could be mitigated by keeping the user active, e.g., by incorporating the user in the decision process about which branch to take next (Huang et al., 2022) or orientation quizzes (Parush et al., 2007; J. Wen et al., 2014). However, these approaches continue to divide the user's attention, and they do not consider individual spatial abilities allowing for personalized assistance, as instruction demand may differ (e.g., Golab et al., 2022). Therefore, further navigation assistance systems supporting active navigation need to be tested and will be presented in this thesis.

Whenever a new navigation system is to be tested empirically, the experiment needs to be designed carefully to avoid potential biases. One obligatory task during the experimental design phase for wayfinding experiments is the selection of one or more experimental routes. The following scenario illustrates problems in the current workflow of finding such experimental routes.

A new professor from the geoinformation domain moves to a foreign country and starts her work at a new university. After several months of setting up the labs and preparing teaching materials, she finally wants to start research. Together with her research group, they developed a novel pedestrian navigation assistance system. They want to test it in real-world environments and meticulously prepare all the navigation conditions and procedures. As the professor is new in this city, she has no historical portfolio of "proven routes" to be used in this study. Therefore, she asks other research groups within the same department for advice. After several emails were sent, the professor received two routes used for several years by other research groups. They are placed in different parts of the city and of different lengths. Furthermore, one of them is a shortest path, and the other is not. Given these differences, the professor gets back to both research groups and asks about the rationale behind the indicated routes. One replies: "It is close to the experimenter's house, and there is a church along the route". The second researcher replies: "The route has five turning points and a length of 700 meters". The professor was not very satisfied with both answers. She started to think about how many routes in the city would meet one of these descriptions. After a network analysis, the professor discovers that millions of possible routes meet these descriptions. Visual inspection discovers great differences between routes fulfilling the same description. One difference regards the average number of branches a wayfinder can select along the route. The angles of intersecting branches at junctions are another difference discovered. Both differences have the potential to impact the wayfinder's behavior during the experiment (e.g., Haque et al., 2007; Fogliaroni et al., 2018; Iftikhar and Luximon, 2023; Dalton, 2003). Two questions come to the professor's mind: (1) How can I select a route in a systematic and reproducible manner? (2) Do different routes considerably impact the study results? If so, how can I control the route's impact on the results?

This short scenario shows two issues in the route selection process in wayfinding experiments. First, many researchers would agree that different routes lead to different results, but there is no systematic work on the impact of route selection on study results. The influence of the street network topology on navigation has been examined (e.g., Amores et al., 2021), but the influence of individual routes has not been scrutinized. Second, there is no framework to facilitate systematic and reproducible route selection for wayfinding experiments. There have been proposed route selection algorithms, however, they usually optimize one characteristic, e.g., the ease of describing navigation instructions for a route (Mark, 1986; Duckham and Kulik, 2003). These procedures are not designed to incorporate the specific needs of researchers while selecting a route for a wayfinding experiment.

Not knowing the influence of route selection on the results of wayfinding studies limits the generalizability of these experiments. Even selecting several routes for a wayfinding experiment does not necessarily solve the problem as the selected routes may produce similar results by chance, and the selected routes are possibly not representative for the experimental area. The results would be meaningful for the tested routes, but their generalizability may be questionable. The selection rationales in the scenario above also show what researchers have in mind while selecting a route, therefore, this process is not random but relatively arbitrary and not reproducible, as many routes would correspond to the descriptions. This is problematic as these selections are based on certain criteria relevant to the research questions, but there still may be differences between these routes with respect to criteria not taken into account. Given these differences, the routes might not be representative for the experimental area. Furthermore, these differences can potentially influence study results. In consequence, there is a need for an approach allowing for the selection of representative routes in a systematic and reproducible manner, as route selection is part of every study requiring a route.

The remainder of this thesis is structured as follows:

1. The related work regarding the problem statement is discussed.
2. The main research questions and aims are defined.
3. The methodology of the conducted research is described.

4. The publications are summarized, and the scientific contribution is highlighted.
5. The full publications, followed by the following sections: Discussion, Conclusion and possible future work, conclude the thesis.

1.2 Related Work

This subsection discusses the relevant literature regarding spatial knowledge and navigation systems. Furthermore, the influence of route selection in wayfinding studies is thematized, together with systematic route selection approaches. This literature overview identifies research gaps, allowing for the derivation of research questions in the next section (see Section 1.3). This subsection provides rather an overview than an all-embracing literature review, as every published or submitted paper has its related work section.

1.2.1 Spatial Knowledge

People learn about their surroundings by directly traversing them (see Anastasiou et al. (2022) for an overview) or interacting with a representation of this space (e.g., map, 3D model, description) (Richter, 2013). This knowledge is used then to find our way in the environment. According to Siegel and White (1975), there are three sequential types of spatial knowledge: *landmark knowledge* - knowledge about unique locations; *route knowledge* - knowledge about landmark sequences forming a route, together with actions needed to go from one landmark to the next one; *survey knowledge* - knowledge about the configurational relations connecting distinct routes and landmarks, forming a more holistic overview of the environment, including topology and metric information. Montello (1998) argues that these three types of spatial knowledge are not necessarily acquired in a strict order.

This argument is supported by empirical evidence showing that these three knowledge types do not build on each other (Moar and Carleton, 1982). The results of Meilinger et al. (2013) suggest that route and survey knowledge are uncorrelated, at least in a familiar environment. The authors hypothesize that the underlying representations of these two types of spatial knowledge are different. Kim and O. Bock (2021) provide empirical evidence against the stage concept of Siegel and White (1975). In their study, participants traversed three routes and subsequently performed spatial knowledge acquisition tasks. This procedure was repeated ten times, and the results showed that landmark, route, and survey knowledge are built in parallel and that the correlations between them increased with every trial.

There is also an ongoing discussion about how spatial knowledge is stored in our minds. Whether it is rather a *cognitive map* (e.g., Tolman, 1948) or rather a *cognitive graph* (e.g., Kuipers, 1982) or a combination of both (MacEachren, 1992; Peer et al., 2021). According to McNamara (2013), spatial knowledge has the following four key properties: (1) *fragmented* - there is detailed knowledge about some areas, whereas knowledge about other areas is of low quality. These areas might be adjacent; (2) *distorted* - remembered distances, angles, and orientations frequently differ from real-world measurements; (3) *hierarchical* - spatial knowledge is organized in categorical and hierarchical units (e.g., X is part of Y); (4) *orientation dependent* - depending on the perspective, spatial relations may be recognized or remembered more efficiently.

Individual differences lead to qualitative differences in the acquired spatial knowledge (Ishikawa and Montello, 2006). Although spatial knowledge can improve with repeated exposure, the literature suggests that accurate metric information about the environment is either acquired during the first exposure or not at all (Moeser, 1988; Ishikawa and Montello, 2006). The learned knowledge about the environment is not always used in the same manner while navigating. In a familiar environment, we can use two different navigation strategies (Dahmani and Bohbot, 2020; Hegarty et al., 2023): (1) spatial-memory strategy (also known as place strategy) in which the wayfinder relies on the acquired spatial knowledge to deduce new paths and positions relative to already known elements of the environment; (2) (stimulus-) response strategy in which the wayfinder takes usual routes following a sequence of actions (e.g., “turn right at the upcoming junction”).

Further literature about spatial knowledge representation will not be discussed, as this thesis deals with the influence of own decisions and engagement with the environment on spatial knowledge acquisition rather than the storage and representation of spatial knowledge in our minds. In the first scenario (see Section 1.1), Bob did not acquire considerable spatial knowledge about the environment he traversed because he blindly followed the turning instructions issued by the navigation system without paying attention to the environment.

1.2.2 Turn-by-Turn Navigation and its Disadvantages

The *turn-by-turn* navigation approach (TBT) is commonly used by pedestrians, car drivers, runners, and cyclists (e.g., Google Maps), and is based on turning instructions issued just before or at a turning point until the destination is reached. The TBT navigation approach can be implemented in a visual (Rümelin et al., 2011), auditory (Xu et al., 2022) or vibrotactile (Lin et al., 2008; Giannopoulos et al., 2015) manner or a combination thereof and comes in different forms and shapes. The turning instruction can be transmitted via an annotated paper map, a digital map-based interface (e.g., Xu et al., 2022) and holograms displayed with augmented reality (AR) technology (Huang et al., 2012; Yount et al., 2022; Qiu et al., 2023), among others. While this navigation approach is efficient in guiding users to their desired destination, there is empirical evidence suggesting the potentially negative effect of navigation assistance systems (mainly implementing the TBT approach) on spatial cognition.

Hejtmánek et al. (2018) investigated the effects of using a GPS-like map on spatial knowledge acquisition and unassisted navigation in a virtual environment. They conclude that spending more time with the map leads to less accurate spatial knowledge. Furthermore, longer map usage times lead to longer walking routes during the unassisted navigation task. Ishikawa (2019) scrutinized the relation between the experience with navigation systems (in-car) and pedestrian wayfinding and spatial knowledge acquisition. Participants with more accumulated experience showed less accurate spatial acquisition with both a digital and a paper map and less efficient wayfinding with a paper map. Ruginski et al. (2019) found a negative influence of GPS usage on spatial transformation processes (mental rotation - Vandenberg and Kuse (1978) and perspective-taking - Kozhevnikov and Hegarty (2001)), which in turn influence visual environmental learning.

The TBT approach can differently influence distinct types of spatial knowledge. Krüger et al. (2004) concluded in their work that TBT navigation fosters landmark knowledge, whereas survey knowledge acquisition is not fully supported. Similar to Ishikawa (2019), Dahmani and Bohbot (2020) assessed the lifetime GPS experience of drivers. They conclude that participants with increased experience have worse spatial memory while navigating unassisted (without GPS). Additionally, they found that increased GPS usage was not bound to a poor self-reported sense of direction, suggesting that increased GPS usage is likely leading to worse spatial memory than vice versa. The results of Dickmann (2012) suggest that car drivers remember more spatial objects along the route with a paper map than with a navigation device. However, nowadays, a paper map is rarely preferred over a digital navigation assistance system by wayfinders. In the experiment of Fenech et al. (2010), participants had to drive a route twice. One group drove the first trial with and the second trial without GPS. The second group did not use GPS in any trial. According to their results, participants with no GPS performed better in the scene recognition task, suggesting that TBT impairs the visual encoding of the environment. On the other hand, in a similar setup, the results of Kelly et al. (2022) suggest that not all types of spatial knowledge may be affected by using navigation assistance systems. Participants with permanent guidance did not perform worse in the route retracing task, a test for route knowledge.

These above-mentioned negative effects on spatial cognition are often attributed to forced attention switches between the environment and the assistance system (Gardony et al., 2013; Gardony et al., 2015) and to the fact that the user is not involved in the decision-making process. Passive instruction following and higher automation levels may lead to less spatial knowledge acquisition (Brügger et al., 2019). The results of Bakdash et al. (2008) suggest that decision-making is crucial for learning a (virtual) environment. Parush et al. (2007) concluded that keeping the user active during the wayfinding task can positively impact spatial knowledge acquisition. Furthermore, the presence of a navigation system impacts the eye-movement behavior by decreasing the share of forward fixations (Brügger et al., 2018), leading to less interaction with the environment.

Given these problems, researchers have proposed modifications to the TBT approach. Enriching the turning instructions with more landmark information (Wunderlich and Gramann, 2021a) or contextual information (Richter and Klippel, 2005; Schwering et al., 2017) is one approach to make TBT more engaging and supporting spatial knowledge acquisition. The environment can also be modified by adding virtual global landmarks, favoring spatial knowledge acquisition (Singh et al., 2021; J. Liu et al., 2022). Another approach is to let the user request information about the surroundings (e.g., points of interest, building floors, weather) (Kota et al., 2010). Another approach to make the user spatially more aware is the schematization of maps (Schmid et al., 2010; Galvao et al., 2020). Involving the user in the path planning procedure (before TBT navigation) can improve survey knowledge and self-orientation, whereas redirecting the user's attention to the environment supports landmark and route knowledge (Lu et al., 2021). In order to overcome the drawbacks of TBT, not only have modifications been proposed, but also approaches reducing the number of turn-by-turn instructions or avoiding them at all.

1.2.3 Alternative Navigation Approaches

While navigating with the TBT approach, the user is required to follow a predefined route with predefined instructions. Alternatives to the TBT approach offer more options to the user, which can actively participate in the decision-making process. In consequence, the discussed alternatives share the feature of not having a completely predefined route. Where applicable, the impact on spatial knowledge acquisition will be reported.

One alternative to the TBT navigation approach is the so-called *beeline navigation*. The working principle is based on the *least-angle strategy* (Hochmair and Frank, 2002), which presumes that wayfinders prefer to select branches with the least angle in relation to the (assumed) destination. The information about the true destination direction can be conveyed by different means, e.g., vibrations, displays, or auditory cues.

There are several implementations of the beeline approach using vibrotactile feedback (e.g., Robinson et al., 2010; Pielot et al., 2011; Dobbelstein et al., 2016). Robinson et al. and Dobbelstein et al. report on successful navigation without imposing a length limit on the walked route. In the experiment of Robinson et al., users walked longer routes compared to the shortest path, 53% (dynamic feedback) and 65% (static feedback) on average. The *PocketNavigator* (Pielot et al., 2012) combines a map-based (OpenStreetMap) navigation system with beeline navigation. The information about the direction was conveyed either visually or visually and by vibrations. The beeline is not pointing towards the destination but towards the next waypoint (similar to Erp et al., 2005). The study (9400 hours of app usage recorded) did not reveal any difference regarding navigation performance between groups (with vs. without vibrotactile feedback).

Savino et al. (2020) compared the beeline approach (also called as-the-crow-flies - ATCF) with TBT for cyclists. A first experiment showed that beeline participants took longer routes on both test routes (25-70%). There was no significant difference between these groups regarding the pointing to the start point task. The TBT approach led to shorter routes, fewer errors and a lower task load. In a second experiment, they compared the initial ATCF system with an enhanced version thereof (ATCF+) that includes visual cues about dead-ends and a mini-map, among others. These enhancements should overcome the drawbacks of the initial system. There were no statistically significant differences between ACTF and ACTF+ regarding route length, the number of errors, task load, or the pointing task.

Albrecht et al. (2016) investigated two audio-based navigation systems. Either the user was guided to the next junction along the route until the destination was reached (*route guidance*) or the audio source was located at the destination and the user had to find an appropriate route (*beacon guidance*). Only the second approach can be considered a beeline approach. The users preferred the first system in unfamiliar environments and if in a hurry. The beeline approach was considered more helpful in known environments and in a tourism scenario. Clemenson et al. (2021) followed a similar beacon approach as Albrecht et al. (2016) but focused on mental map creation in their research. They compared their *soundscape* approach with verbal TBT instructions on a scavenger hunt with five points of interest on the Microsoft campus. Both systems were tested by participants unfamiliar (naïve) and familiar (experts) with the experimental area. Two tasks to assess spatial learning were employed; (1) pointing to five points of interest; (2) placing these 5 POIs on a simplified map. The soundscape system helped naïve users to perform better in both tasks, compared to naïve users with verbal TBT instructions. In the expert group, no improvement was found.

Kuo et al. (2020) compared four navigation systems in a virtual environment: traditional map-based TBT, augmented reality (AR) TBT, AR orientation-based (arrow pointing to the destination + distance information) and reference-based (enriched turning instructions regarding one reference object, a Ferris wheel). The orientation-based approach uses the beeline method. Using a within-subject design, every participant had to navigate four routes twice, once with and once without an assistance system. While navigating without further assistance, if participants felt lost, they were allowed to check a smartphone to receive navigation instructions. In the first experiment (with a navigation system), users of the reference-based method had significantly longer completion times than all other navigation approaches. The travel distance was similar in all conditions. In the second experiment (without any navigation system but smartphone consultations allowed), participants who had previously followed reference-based guidance had the shortest completion times and route length, whereas orientation-based users had the longest. Former reference-based users were less dependent on smartphone hints (overall phone-checking time) than TBT (map-based and AR) users. Former reference-based users rated the task difficulty lower than users of the other three navigation approaches. Only participants who had used the reference-based method could improve their route length compared to the assisted trial, i.e., the potential benefit of this system was only visible in the second independent task.

Willamowski et al. (2022) proposed a smartwach-based navigation system for runners (*FlexNav*) that defines *runnable zones*. In these zones, the runner can freely explore the surroundings. Between the zones, the runner is required to follow a predefined path. After the trials with FlexNav, 26 participants had to place 12 intersections on a map, thereof 6 in runnable zones. The results suggest that less navigation support (runnable zones) may stimulate spatial learning.

Huang et al. (2022) proposed a navigation system supporting the free exploration of the environment. The system defines a so-called *Potential Route Area* (PRA), which encompasses all possible routes from the current location to the destination no longer than a predefined threshold. This area is updated frequently and highlighted on a digital map with landmarks, and no further instructions are given. The underlying concept assumes that the destination will be reached within the predefined distance threshold as long as the user is within the PRA. A user study showed that, compared to Google Maps participants, users of the PRA system drew better sketch maps in terms of survey likeness and route likeness (Krukar et al., 2018). The performance in the orientation task (pointing to the starting point) and the number of drawn points of interest in the sketch map did not reveal a significant difference between both groups.

Although there are approaches tackling the problem of divided attention between the device and the environment, none of the proposed systems takes the spatial abilities of the users into account to personalize the navigation experience. This step would allow finding a compromise between free exploration supporting spatial knowledge acquisition and a maximum allowed walking distance while reaching the destination. Furthermore, the discussed beeline implementations can be realized with augmented reality (AR) and potentially improve spatial knowledge acquisition as the destination can be placed directly in the real world. These two approaches will be part of the thesis. The AR-based approach potentially allows for more goal-directed navigation than auditory cues (Dobbelstein et al., 2016).

1.2.4 Influence of Route Selection in Comparative Wayfinding Studies

In this subsection, wayfinding studies with more than one route are discussed regarding whether the route was considered an independent variable in the analysis. The discussion will shed light on how the potential influence of routes is considered during analysis. This subsection will exemplify both the consideration and the negligence of the impact routes may have on study results.

Savino et al. (2020) compared two navigation systems for cyclists on two different routes. They considered the potential influence of the route on study results and analyzed data for each route separately. The analysis of both data sets led to the same conclusions regarding route length, task load, and orientation, but the number and the types of errors made differed for both routes. Liao et al. (2019) tried to predict (machine learning) user tasks from eye-tracking data collected on two different routes. They were mindful of the potential influence of the routes, and the results suggested that the used learning algorithm might have learned the features of both routes. Using data from one route and predicting the other yielded different accuracies depending on the training set (route). Sönmez and Önder (2019) scrutinized the perception of the environment with two navigation approaches on two routes in Istanbul, Turkey. As both routes and their respective environments are different, the authors analyze the data for both routes separately, revealing no difference in the number of drawn items (sketch map) between both navigation conditions, however, it is important to keep in mind that participants were told before the experiment that they would have to draw a sketch map afterward. This circumstance may have impacted the study results considerably. Stefanucci et al.

(2022) compared four navigation system scenarios in two different virtual environments with one route each. Before the analysis, they performed t-tests comparing duration and pointing errors for both routes. As they found no difference, they excluded the environment (route) as a factor.

Dong et al. (2021) compared two navigation systems for pedestrians on three different routes on the campus of Beijing University of Posts and Telecommunications. They treated the route as a factor in an ANOVA analysis. The route had no significant effect on any of the scrutinized eye-tracking indicators. Only the influence on duration was significant, but this was expected as routes had different lengths. However, during further sketch map analysis (logistic regression), the route was no longer considered a potential factor. Kuo et al. (2020) compared four navigation systems on four different routes in a virtual environment. They classified the route from easy (three turns) to difficult (six turns). Although the authors expected the route to impact navigation performance, the results did not mention this variable. Therefore, it is unclear whether the route impacted the study results. Thi Minh Tran and Parker (2020) compared three AR-based navigation systems in a virtual environment on three different routes. Each route was of equal length and had the same number of turning points and junctions. One navigation system was assigned to exactly one route. In consequence, it remains unclear whether the presented results are an effect of the navigation system, the route, or the interplay of both. Ishikawa et al. (2008) compared three navigation conditions on six short routes (144–298 m), each having three turns. Their analysis did not scrutinize whether the route influenced the participant's behavior (e.g., number of stops or sketch map accuracy).

As discussed, there are works in which the route is considered an important variable and treated explicitly in the analysis. We saw as well the potential impact of routes on study results. Sometimes the routes may lead to the same result, but this may be by chance. On the other hand, routes are not always given importance, although they may impact study results. Given the vast amount of possible routes and their potential impact on study results, a systematic approach for route selection is desirable.

1.2.5 Systematic Route Selection

Given that there are millions of possible routes in areas of non-trivial size, a route selection procedure is needed. All the more because of their potential influence on study results (see Section 1.2.4). Usually, existing procedures are limited to one start-destination pair, and they find optimal routes regarding one or more criteria. In the navigation domain, not only the shortest path (e.g., Ishikawa and Takahashi, 2014; De Cock et al., 2019) but also the fastest (e.g., Gonzalez et al., 2007) or the most scenic route (e.g., Hochmair and Navratil, 2008; Gavalas et al., 2017) may be of interest for a wayfinding experiment.

Mark (1986) proposed an approach to find routes that balance the route length and the instruction complexity along the route's junctions. Continuing this work, Duckham and Kulik (2003) adapted the instruction complexity measure and introduced the *simplest* path, allowing for finding routes with the least instruction complexity without considering the route length. Their simplest paths were, on average, 16% longer than the shortest paths. Based on this work, Richter and Duckham (2008) integrated spatial chunking (Klippel et al., 2003), and extended characteristics of instructions such as landmarks or ambiguities. Routes selected by this approach achieved shorter descriptions than the shortest and simplest paths proposed by Duckham and Kulik (2003). Another approach concentrating on optimizing one particular aspect was proposed by Krisp and Keler (2015). Their procedure finds routes between a start and end node, avoiding complicated crossings. Multi-criteria approaches have also been proposed to find optimal routes regarding different route attributes, allowing for finding compromises. Chakraborty et al. (2005) proposed a genetic algorithm recommending several near-optimal alternative routes between given start and end points. Kriegel et al. (2010) used skyline queries optimizing for different features such as gas consumption and the number of traffic lights. They proposed an algorithm capable of handling large graphs (170 000 nodes). Here, again, start and end points need to be selected apriori. J. D. Bock and Verstockt (2021) developed a two-step route recommendation framework based on multiple criteria. The researcher assigns a weighting configuration consisting of a positive or negative impact sign and a factor for each criterion. First, the framework ranks a set of predefined routes between the same two points selected by the user. These routes come from the route provider TomTom. Second, waypoints are added to the most suitable predefined route to find potentially more suitable routes by minor deviations. With this step, the framework tries to decrease the dependency on the route provider.

These discussed approaches are limited to one preselected start-destination pair and do not recommend other start-destination pairs in the experimental area. This circumstance can be desirable if research constraints limit the start and end points of a wayfinding experiment. However, this limitation may introduce the potential bias of having selected a route that is not representative for the experimental area, and in consequence, impact study results. If a selected route is considerably distinct from most routes in the experimental area, the results may not be generalizable. However, none of the discussed approaches was designed to find routes representative for the experimental area, allowing for potentially more generalizable results.

1.3 Main Research Questions

This subsection will present the main research questions of this thesis, together with the rationale behind each of them.

Given the lack of systematic knowledge about the potential influence of route selection on wayfinding study results, investigating this effect is of utmost importance. The literature (see Section 1.2.4) provides examples in which route selection impacted study results, as well as studies in which the outcome remained unchanged across routes. The tested routes may have been similar enough to produce similar results, but this may also have happened by chance. Therefore, the first research question is:

RQ1: Does the route selection influence study results?

Given the vast amount of possible routes in any experimental area of non-trivial size, there is a research gap in providing a methodological approach for systematic and reproducible route selection without preselecting the start and end point, as this may already introduce the potential bias described above. Finding one route in a systematic and reproducible manner does not necessarily mitigate the problem of potential bias caused by route selection. It would also be desirable to select routes that represent the given experimental area as best as possible. These steps can be combined into a methodological approach, e.g., a route selection framework, that should be able to find routes that are similar to other routes in a systematic and reproducible manner. This would allow for more transferable results, since the selected routes are similar to most routes in the experimental area. Of course, routes can be described by various characteristics (e.g., the number of turns and the variation of terrain slope). Therefore, features describing the potential routes in the experimental area need to be preselected to define the basis for similarity. The selection of features characterizing the routes needs to be adapted to the research questions for a given experiment, e.g., the average number of landmarks for an experiment scrutinizing spatial knowledge acquisition. Therefore, the second research question is:

RQ2: Can we select representative routes for wayfinding experiments in a systematic and reproducible manner given an experimental area?

If we can find similar routes within an experimental area, this approach can be extended beyond the original experimental area and allow for finding similar routes in other geographic areas. This would facilitate the replication of wayfinding studies and provide one step towards more comparable results of wayfinding studies across different experimental areas. In an ideal world with features perfectly describing routes, two similar routes should lead to similar results if other variables are kept constant. From this assumption, the following research question originates:

RQ3: Can we find routes in other geographic regions that can potentially produce similar study results as the original route?

The last research question regarding route selection concerns the sample size in wayfinding experiments. As sample sizes vary considerably in wayfinding experiments (e.g., Singh et al., 2021; Golab et al., 2022), they could impact study results together with the selected route. If this is the case, then routes providing stable results across different sample sizes are desired. Assuming that route selection impacts study results, the following research question arises:

RQ4: Does the effect of route selection on study results differ for different sample sizes?

As we have seen, there is empirical evidence that wayfinding systems, in their current form, may be adverse to spatial cognition (see Section 1.2.2). There is work suggesting that keeping the user active may improve spatial knowledge acquisition (Parush et al., 2007; J. Wen et al., 2014; Clemenson et al., 2021). On the other hand, there is also literature that does not confirm these findings entirely (Kelly et al., 2022; Huang et al., 2022). Given these differences, it becomes apparent that more research in this direction is needed. This thesis contributes to this ongoing discussion by designing and evaluating two navigation systems that encourage the user to engage with the environment in order to make own decisions along the route. Therefore, the following research question becomes evident:

RQ5: Does more decision-making freedom and engagement with the environment lead to improved spatial knowledge acquisition?

There is also an ongoing discussion if new navigation systems should be developed and if they should focus on spatial knowledge acquisition, as current navigation systems already provide the primarily requested functionality of a navigation system, which is successful guidance to a selected destination. The thesis will contribute to this discussion with the following research question:

RQ6: Are people willing to take longer routes if they have more freedom to make decisions along the route or learn more about the environment?

With the answer to this question, navigation system users may express their subjective importance regarding predefined routes and spatial knowledge acquisition. This will shed light on whether this research direction should be followed further.

1.4 Aims of the Thesis

In this subsection, the aims of this thesis are presented. They are tightly related to the main research questions (see Section 1.3) and the research gaps shown in Section 1.2.

The first aim is to investigate whether different routes lead to different study results. This aspect will be scrutinized by means of an agent-based simulation study in the city center of Vienna, Austria (see Section 1.5.1). On potential routes in the experimental area, two navigation approaches will be compared with respect to their arrival rate. This experiment not only sheds light on the differences produced by different routes but will also provide information about the shares of routes leading to contradictory results. The hypothesis is that there are routes leading to contradictory results, meaning that the result of a study may depend on route selection. As the sample size in wayfinding studies may vary considerably (e.g., Thi Minh Tran and Parker, 2020; Golab et al., 2022), different sample sizes (N = 15, 25, 50, 3000 agents) will be tested in the simulation to scrutinize whether the effect of route selection on study results differs for different sample sizes, i.e., arrival rates for the same routes will be compared across different sample sizes.

The second aim of this thesis is to develop a route selection framework for wayfinding studies to support informed route selection. Routes can be described with different characteristics, therefore, the framework should be flexible enough to incorporate important information for the given wayfinding study (e.g., points of interest in a study about spatial knowledge acquisition). It will assist in systematic and reproducible route selection. Furthermore, it would also be desirable to have frequent routes in a given area, similar to many other routes. Therefore, the framework will be able to find routes similar to a hypothetical *average* route in the experimental area. This should allow for more generalizable study results. Having such a framework would provide several advantages to the research community:

- **Ecological validity** - selecting an arbitrary route carries the risk that it has unusual characteristics for the experimental area, i.e., that it is not representative. Therefore, choosing a route similar to most routes in the study area should lead to generalizable results for the entire area.
- **Replication** - as of today, wayfinding studies conducted in real-world environments are not replicated in other geographic areas. One possible reason for this status quo can be the difficulty of finding similar routes in different real-world environments. The route selection framework will be able to find similar routes both within the experimental area and in different geographic areas. Conducting a wayfinding experiment in two countries on similar routes would allow validation of the results and may reveal cultural differences in navigation.
- **Comparison** - in many wayfinding studies, the widespread map-based *turn-by-turn* (TBT) approach acts as the baseline (e.g., Giannopoulos et al., 2015; Huang et al., 2022), therefore, a considerable amount of data is potentially available. If we find similar routes, we could estimate the performance for routes alike. If these estimates are robust, running this condition may become superfluous.

These first two aims can be combined into a third objective: selecting routes leading to similar results across sample sizes that are likely to be compatible with most routes. Such a procedure will be proposed as well in this thesis and aims for more generalizable study results, as the selected route should lead to similar results as most routes.

Keeping the user active and redirecting the user's attention to the environment has the potential for supporting spatial knowledge acquisition (Lu et al., 2021). Given this potential and possible adverse effects of current navigation systems on spatial cognition (see Section 1.2.2), the fourth aim of this thesis is to investigate whether participation in the decision-making process along the route will foster spatial knowledge acquisition and users' spatial awareness. Therefore, two novel navigation approaches encouraging the user to make own decisions will be proposed.

Although both navigation systems encourage users to make own decisions along the route, the two navigation approaches differ considerably. One system will give personalized support based on environmental spatial abilities coming from a standardized questionnaire filled out before the experiment. The same system provides information about the destination only at the beginning, whereas the second system provides a permanent visualization of the destination. Therefore, in one system, the user needs to reorient frequently, whereas, in the second system, the user always knows where the destination is located. Furthermore, both novel navigation approaches differ in their automation levels. One system occasionally gives instructions along the route, while the second proposed system never provides information about which branch to take next. This contrasts the turn-by-turn navigation approach, which assists the user at every turning point (full support). As outlined, own decisions made by the wayfinder are the core idea of both systems, but additional features (e.g., destination visibility) are scrutinized (see Section 1.6 for more details). Both proposed navigation approaches limit potential distractions and encourage the user to make own decisions while interacting with the environment. These circumstances are expected to support spatial knowledge acquisition (Ishikawa et al., 2008; Meade et al., 2019).

Both systems will be compared against the classic turn-by-turn approach regarding spatial knowledge acquisition, arrival rate, workload, and user experience. The acquired spatial knowledge will be tested with a series of tasks, e.g., pointing to the start point, retracing the walked route on a map and drawing in remembered points of interest on a map. These navigation assistance systems will be tested in real-world urban environments on the outskirts of Vienna, Austria. This study will contribute to the discussion of whether active wayfinders acquire more spatial knowledge about their surroundings, as there is no complete accordance in the literature (e.g., Parush et al., 2007; Kelly et al., 2022). In the same study, in a pre-experiment phase, participants will be asked whether they would accept walking longer routes between start and destination if this would result in more spatial knowledge acquisition. This data will show whether wayfinders would appreciate a navigation system having an additional feature besides guiding to the destination. The last aim of the thesis is to contribute to the ongoing discussion on whether current navigation assistance systems have an adverse effect on spatial knowledge acquisition (e.g., Ishikawa et al., 2008; Fenech et al., 2010; Hejtmánek et al., 2018). Given the experiment setup, conclusions about short-term effects can be drawn.

1.5 Methodology

This subsection presents the methodology used to answer the research questions (see Section 1.3). It includes agent-based simulations, standardized questionnaires, and in-situ wayfinding studies with spatial knowledge acquisition tasks.

1.5.1 Agent-based Simulations

Simulating human navigation can have many advantages. It allows the testing of novel navigation systems before implementing the first real-world prototype. On the other hand, in certain scenarios, a real-world experiment with human subjects would be infeasible due to limited resources. Furthermore, simulations allow testing a multitude of possible scenarios. Different aspects influencing human wayfinding such as uncertainty (e.g., Jonietz and Kiefer, 2017), visual attention (e.g., Schrom-Feiertag et al., 2016), herd behavior (e.g., Vizzari et al., 2020), affordances (e.g., Raubal, 2001), spatial cognition (e.g., Kielar et al., 2016), and landmarks (e.g., Filomena and Verstegen, 2021) can be modeled with agent-based simulations. Many agent-based simulations are focussed on indoor spaces (e.g., Raubal, 2001; Hajibabai et al., 2007; Schrom-Feiertag et al., 2016). Agent-based simulations can be of different granularity levels. Fine-grained simulations focus on details such as obstacles, signage or doors (e.g., Hajibabai et al., 2007; Karmakharm et al., 2010; Vizzari et al., 2020), whereas other simulations mainly focus on the street network (e.g., Filomena and Verstegen, 2021; Amores et al., 2021; Savino et al., 2022).

Amores et al. (2021) and Savino et al. (2022) are examples of using agent-based simulation for collecting data that otherwise would have been very time-consuming. Amores et al. (2021) tested a novel navigation approach for car drivers on 13500 routes in three cities, also analyzing the influence of the city's topology on navigation performance. Savino et al. (2022) simulated the beeline navigation approach (least-angle strategy) for cyclists on 10000 routes in 1633 cities worldwide. They identified street network features favoring successful beeline navigation. Both studies focus on the city's topology and features describing the city as a graph, but they have not scrutinized the impact a single route may have on study results.

In this thesis, all potential routes within an experimental area should be traversed with a certain navigation system to see their potential impact on study results. As, depending on the criteria, there are thousands or millions of candidate routes, an agent-based simulation approach will be employed to investigate the potential impact route selection may have on study results. Computing all potential routes in a given experimental area is an NP-complete problem (see Chapter 10), however, the population of possible routes can be limited with criteria such as length (Euclidean distance) or the number of junctions along the route.

The agent-based simulation will also be used to verify the viability of one of the proposed novel navigation approaches. Only one of the approaches will be verified with a simulation study, as the underlying approach of the second proposed navigation system (beeline navigation) has already been studied (Hochmair and Frank, 2002). One possible benefit of these navigation approaches is improved spatial knowledge acquisition. Several models for agent-based simulations integrating spatial cognition have been proposed (Raubal, 2001; Kielar et al., 2016; Schrom-Feiertag et al., 2016; Jonietz and Kiefer, 2017). This aspect, however, was not modeled in this thesis, as the aim of the simulation was, in the first place, to gain insights about the viability of the novel navigation approach. Although agent-based simulations are a valuable research tool, it has to be kept in mind that a model is always a simplification of reality and may not be modeled adequately.

1.5.2 Wayfinding Studies

Studies about different aspects of wayfinding can be conducted either by means of simulations (see Section 1.5.1), in real-world settings (e.g., Golab et al., 2022; Kapaj et al., 2022), virtual environments (e.g., Kuliga et al., 2020; Gath-Morad et al., 2021), or with the aid of questionnaires (e.g., Lawton and Kallai, 2002; Montello and Xiao, 2011). Dong et al. (2022) compared the wayfinding behavior of pedestrians in a virtual and a real environment. Although the wayfinding performance was comparable in both environments, they were differences in visual attention and distance estimation. After considering the advantages and disadvantages, and given the potential differences, a real-world experiment on the outskirts of Vienna was designed to evaluate the two novel navigation systems. They were compared against the classic TBT approach regarding spatial knowledge acquisition, arrival rate, walking distance, workload, and user experience (see Section 1.5.3).

Spatial Knowledge Acquisition Tasks

Since there are different types of spatial knowledge (see Section 1.2.1), there are different tasks to approximate each of them. This subsection gives a brief overview of how the acquired spatial knowledge can be tested after a wayfinding task and is by no means exhaustive. Landmark knowledge can be tested by deciding whether a scene has been seen during navigation (scene recognition task - e.g., Lu et al., 2021; Sugimoto et al., 2022; Kim and O. Bock, 2021) or by enumerating points of interest (e.g., Sugimoto et al., 2022). The acquired route knowledge of study participants can be tested by walking the same route back from the destination to the starting point (e.g., Brügger et al., 2019) or by traversing the same route without assistance (e.g., Meade et al., 2019; Kelly et al., 2022). Furthermore, this type of spatial knowledge can be assessed by indicating the sequence of actions (left, right and non-turn) along the route (e.g., Kuil et al., 2021), by ordering pictures of junctions or landmarks (e.g., Kim and O. Bock, 2021), or by indicating the executed action at the depicted junction (e.g., Kuil et al., 2021; Lu et al., 2021). Survey knowledge (also called configuration knowledge) is assessed by pointing to different locations (e.g., W. Wen et al., 2013; Kuil et al., 2021; Kim and O. Bock, 2021; Stefanucci et al., 2022). This task is also called the judgment of relative direction task and can be executed physically or by using additional devices. The placement of locations (landmarks and junctions) on a map is another task to assess survey knowledge (e.g., Kuil et al., 2021; B. Liu et al., 2022). The same type of spatial knowledge is approximated by estimating distances between locations (e.g., Kuil et al., 2021). Two widespread tasks are drawing the walked route on a map (e.g., Lu et al., 2021; Kim and O. Bock, 2021) and drawing a sketch map of the traversed environment on a blank sheet of paper (e.g., Ishikawa and Montello, 2006; J. Liu et al., 2022). However, the analysis of sketch maps is not a trivial task, as they can be analyzed along many dimensions (see Hátlová and Hanus (2020) for an overview). For example, they can be assessed according to their route- and survey-likeness (Krukar et al., 2018), cartographic generalization (Manivannan et al., 2022), or alignment with metric maps (Schwering et al., 2014).

Depending on the exact setup of the task approximating spatial knowledge, more than one type of spatial knowledge can be tested or rather a mix thereof. Due to modifications following the underlying research questions, the tasks do not need to be always comparable. In this thesis, the following tasks were employed to assess the acquired spatial knowledge of the participants: (1) Pointing to the start point; (2) Estimation of the walking distance (meters); (3) Abstract route drawing - drawing the sequence of turns and crossed junctions (i.e., non-turns); (4) Retracing the walked route on a map; (5) Draw recalled points of interest (POI) on the same map. Further details about these tasks can be found in

Chapters 7 and 8.

1.5.3 Standardized Questionnaires

Standardized questionnaires are often used in studies to collect data about the user's workload or experience. The questionnaires described below were employed and analyzed in the user study.

The raw NASA Task Load Index (NASA TLX) is a questionnaire measuring the subjective workload after conducting a task (Hart and Staveland, 1988). It has six subdimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration level. To each of these subdimensions, a score between 1 and 20, ranging from very low to very high or from perfect to failure, can be assigned. Lower scores indicate a lower workload. It has been used in wayfinding studies (e.g., Rehrl et al., 2014; Wunderlich and Gramann, 2021b; B. Liu et al., 2022; Huang et al., 2022). This questionnaire was also used in the presented study because increased mental load was expected due to the incorporation of the user in the decision-making process.

Another frequently used questionnaire is the Santa Barbara Sense of Direction Scale (SBSOD) (Hegarty et al., 2002). It is a self-reported scale for environmental spatial abilities, consisting of 15 questions. Participants had to decide to which degree they agree with positively (e.g., "I am very good at judging distances.") and negatively (e.g., "It's not important to me to know where I am.") framed questions. The higher the score, the better the participant's self-estimation. In previous works, the correlation between this scale and performance in spatial tasks has been shown (e.g., Nori and Piccardi, 2015; Anacta, 2020). Therefore, this data was collected during the experiment to ensure that the observed differences in arrival rate, walking distance, spatial knowledge acquisition, workload, and user experience come from the navigation system and not from the user's environmental spatial abilities. Furthermore, this data was an input for one of the proposed navigation assistance systems.

Two further questionnaires regarding the system's usability (SUS - Brooke, 1996) and the user experience (UEQ - Laugwitz et al., 2008) were used in the real-world experiment. The System Usability Scale (SUS) consists of 10 questions regarding how easy it is to use and learn the system at hand (5-Point Likert Scale). The higher the score, the better the system performs regarding usability (Sauro and Lewis, 2012). The format of the User Experience Questionnaire (UEQ) is a semantic differential comprising 26 adjectives and their corresponding antonyms. The participant decides on a 7-Point Likert scale which adjective of the adjectives pair (e.g., boring – exciting and clear – confusing) describes the system better. The UEQ has six factors: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. Again, the higher the scores, the better the participant's experience. Both questionnaires were used in wayfinding studies to evaluate a navigation system (Rehrl et al., 2014; Giannopoulos et al., 2015; Rudi et al., 2016; Gerstweiler et al., 2018; Stähli et al., 2020). Both questionnaires were employed in the real-world study to gather insights about usability and user experience, and potential future improvements of both navigation systems.

1.6 Summary of Published Articles

This subsection will summarize all published and submitted articles. The research questions addressed in each article will be emphasized. Furthermore, the connection between the articles is highlighted.

1.6.1 Not Arbitrary, Systematic! Average-Based Route Selection for Navigation Experiments

Potentially, there are millions of possible routes in a given experimental area. Therefore, selecting one or more experiment routes is not a trivial task. Furthermore, it would be desirable that the selected route(s) reflect the characteristics of the entire experimental area to render the results more generalizable. This article, first, reviewed rationales and justifications for selected routes in wayfinding experiments, and second, proposed a framework for systematic route selection reflecting average characteristics of the experimental area.

A review of six major journals and conferences (AGILE, COSIT, GIScience, IJGIS, LBS and SCC) from 2010 to 2020 showed rather poor justifications for the selected routes in navigation experiments. The route description often omitted even basic route properties such as length, type of environment or the number of decision points. Only articles with wayfinding tasks for participants and studies presenting predefined routes were screened. The selection of the six mentioned sources was by no means exhaustive, but it provided an insight into the route selection process and the importance given to it. It also left the impression that the selected routes originated from ad-hoc decisions. This circumstance causes two problems: First, it represents a barrier to replicate a study, as similar routes cannot be identified given the lack of described route features. Second, the selected route might unintentionally be a particular case rarely present in the experimental area. This would limit the generalizability of the study results.

Therefore, this article addressed **RQ2** by proposing a framework for systematic and reproducible route selection. Furthermore, the selected routes try to be as similar as possible to a hypothetical average route. To measure route similarity, first, features describing a route needed to be defined. This article used features such as the average number of options at a decision point, the number of right, left, and non-turns along the route, land cover and terrain slope to describe routes. Depending on research questions and experimental design, this list can be extended by features essential to the researcher. The hypothetical average route contains the average value for each route feature (e.g., the number of left turns) based on the entire route population in the experimental area. The distance between this route and every potential route was calculated with the weighted Euclidean distance. The route features can be assigned weights to reflect importance. All potential routes, which can be limited by length or the number of decision points, were then ranked according to their distance to the average route. The lower the distance, the more similar the compared routes.

The viability of this approach was demonstrated with both synthetic and real-world data. The results of three synthetic scenarios showed the expected results according to the presented framework. The results of the scenario with real-world data from two different environments (city center and residential area) in Vienna, Austria, showed the ability of the proposed framework to find routes as close as possible to a route reflecting global averages of the experimental area. The framework supports informed route selection during experimental design for wayfinding studies. Furthermore, it contributes to the replicability of wayfinding studies as route features are made explicit while using the framework. It potentially allows for finding similar routes in other geographic areas. This claim will be scrutinized in the two following articles (see Sections 1.6.2 and 1.6.3).

1.6.2 Route Selection – From Replication to Recreation

This article is an extension of the original route selection framework paper. The route selection framework was originally designed for wayfinding studies involving pedestrians. In this article, the framework's suitability for cyclists was demonstrated, addressing as well **RQ2**. Beyond highlighting the potential application scenarios for cyclists (and other users of public space), the article showed how to find similar routes in different geographic areas, whereas the original work focused on finding representative routes within one given experimental area. The ease of exchanging the target route (hypothetical average route or another existing route) showed the flexibility of the route selection framework. Although similar routes in Vienna (Austria), Florence (Italy) and Bremen (Germany) were found, it remained unclear whether they would lead to similar results. This research question will be addressed in the following article. If similar routes (according to the framework) lead to similar results, the framework will show additional value beyond supporting informed route selection in wayfinding studies.

1.6.3 Replication of Wayfinding Studies in Different Geographic Areas. A Simulation Study

This article addressed **RQ3**, as it verified whether routes in other geographic areas that are likely to produce similar results to the original route in an experimental area could be found. The replication of wayfinding studies is mainly limited to questionnaire-based studies (e.g., Lawton and Kallai, 2002; Montello and Xiao, 2011). This circumstance may be caused by the difficulty of finding similar routes in other geographic areas. The previously introduced route selection framework (see Section 1.6.1) claimed to mitigate this problem. On similar routes (according to the framework), similar results regarding a selected metric (e.g., arrival rate) were expected.

Therefore, first, the route reflecting best the city center of Vienna, Austria, was selected. Second, the five most similar and the five least similar routes from the Western part of Djibouti City were identified with the framework. As a real-world study would be resource-intensive, an agent-based simulation was employed. On every selected route in both environments, agents navigated with two different navigation systems: turn-by-turn (TBT) and Free Choice Navigation (FCN). In TBT, agents were supposed to follow a predefined route while getting instructions at turning points. In the FCN approach, agents had to make own decisions about which branch to take next while occasionally getting instructions at turning points (see Section 1.6.5). Therefore, FCN agents will stick less to the predefined path and explore the experimental area more. Both navigation systems were compared regarding the success rate. An agent was successful if the destination was reached with a route no longer than 150% of the shortest path. To limit the population of potential routes, only the shortest paths with 12 decision points and a length between 550 m and 1000 m were considered.

In Vienna, there were four routes with a minimal weighted Euclidean distance of 0.12 to the hypothetical average route. As none of them could be identified as more suitable than the others, all four routes in Vienna were considered in the simulation study. For each route in Vienna, the framework calculated the five most and the five least similar routes in Djibouti City. Six thousand agents navigated each of these routes either with TBT or FCN. Suppose the framework was capable of finding similar routes in different geographic areas. In that case, the most similar routes in Djibouti should have yielded more similar arrival rates to those in Vienna compared to the five least similar routes in Djibouti City. For the TBT approach, more similar routes (according to the framework) in Djibouti City yielded more similar results to those from Vienna than less similar routes in Djibouti City. This suggests the suitability of the framework to find similar routes in different areas for the TBT approach. In the case of FCN, different results were observed, as less similar routes in Djibouti city yielded more similar arrival rates to those in Vienna than more similar routes. The potential explanation is that FCN agents were more likely to take different routes and, by this, explored the environment more. However, the features described only the route itself but not the neighborhood, which should be considered for navigation systems supporting free exploration. Taken together, for the widespread TBT approach, the route selection framework is a first step towards easier replication of wayfinding studies in different geographic areas. Moreover, the obtained results suggest a potentially considerable influence of routes on study results. This aspect will be scrutinized systematically in the following article.

1.6.4 Rethinking Route Choices! On the Importance of Route Selection in Wayfinding Experiments

The previously summarized articles focussed on systematic route selection, replicability, and finding similar routes. However, the remaining question is whether route selection has the potential to influence study results considerably (**RQ1**). Many researchers would agree that arbitrary route selection for a wayfinding experiment could impact the results. This article systematically scrutinized the potential impact of all routes in the experimental area (city center of Vienna) on study results. This is all the more important, as we have seen previously (see Section 1.6.1), that route selection is not always given importance because only a few details about the selected routes are made explicit. Therefore, there is a chance that the selected route for a wayfinding study considerably influences the study outcome.

In order to gain insights about this influence (**RQ1**), again, an agent-based simulation study comparing TBT and FCN regarding the arrival rate was employed (see Section 1.6.1). The exact details of both navigation systems are not relevant for this summary. The important point is that they support the user differently while reaching the destination. In this study, four different sample sizes ($N = 15, 25, 50, 3000$) were tested to see whether the sample size impacts the route influence on study results, i.e., whether the arrival rate on a route changes with the sample size, thus addressing **RQ4**. Both systems showed a stable success rate (share of successful agents) across sample sizes (TBT - around 97%; FCN - around 90%). The average difference (subtracting the FCN success rate from TBT) between the two systems varied slightly across sample sizes (between 5.7% and 7.7%), suggesting the superiority of TBT regarding the success rate. At first glance, this result gives the erroneous impression that route selection is not crucial, as the trend (TBT better than FCN) was maintained across sample sizes. However, the minimum difference ($TBT - FCN$) is a negative value, meaning that there was at least one route on which FCN was more successful than TBT. Therefore, route-wise differences were examined. Here, another picture was drawn across sample sizes. With $N = 3000$, around 8% of the tested routes led to results contradicting the global trend, i.e., the FCN navigation system was equally or more successful than TBT on these routes. This share increased with decreasing sample size ($N = 50$ - 16%, $N = 25$ - 30%, $N = 15$ - 47%).

These results revealed the potential influence of routes on study results. Depending on the selected route, the study results may be contradictory. The share of routes causing contradictory results increases with decreasing sample size. Therefore, ad-hoc decisions for route selection should be avoided. In consequence, this article proposed an approach to select suitable routes. It is a two-step filtering process. First, routes with consistent success rates across all four sample sizes are selected. Second, routes are chosen in line with the global trend (aka population mean). The given list of suitable routes can be ranked with the route selection framework introduced earlier (see Section 1.6.1).

1.6.5 Navigating Your Way! Increasing the Freedom of Choice During Wayfinding

As shown in Section 1.2.2 navigation assistance system may adversely impact spatial cognition. This is often attributed to forced attention switches (Gardony et al., 2013) and blindly following a predefined route (Lu et al., 2021) like in the turn-by-burn (TBT) navigation approach. Therefore, this article proposed a novel navigation approach, called *Free Choice Navigation* (FCN), trying to balance the number of free choices, route length and the number of instructions given. The idea behind FCN was to involve the user in the decision-making process and engage the user more with the environment. This article was the foundation for **RQ5** but did not address spatial knowledge acquisition directly, as this aspect was not modeled in the agent-based simulation study. To test the viability of this approach, an agent-based simulation study with 6000 agents (between-subject design) in 3 different cities comparing two navigation systems (FCN and TBT) was employed. In every city, having a different network topology (Thompson et al., 2020), 100 random routes with a length between 500 m and 5000 m were selected. An agent was successful if the route to the destination was no longer than 150% of the shortest path.

One tested navigation system was the widespread TBT navigation approach in which the agent received navigation instructions at turning points. Agents using this navigation system had the ability to follow a navigation instruction correctly, meaning that errors could occur. The mechanics of the FCN approach are more complex and need to be explained in more detail. At the beginning, every FCN agent received two pieces of information: the beeline distance and the direction to the destination. While the agent was walking towards the destination, the system estimated if the agent needed an instruction or if it was still well-oriented to make reasonable decisions. This estimation was based on agent traits such as environmental spatial abilities, spatial confidence, and the ability to follow instructions correctly. Furthermore, the environmental complexity of junctions was taken into account by the FCN navigation system. The system did not give any help at the first two junctions the agent traversed, as at this point, the agent should be oriented well. Orientation, in this case, referred to the subjective direction in which the agent believed the destination was located. The agent's orientation was modeled based on environmental spatial abilities and time (the number of traversed junctions). The lower these abilities and the more the agent walked, the worse the agent's orientation. Based on this orientation and the agent's spatial confidence, staying at a junction, the agent determined which branch to take next toward the destination (based on the least-angle strategy). Based on this information known to the system, FCN decided if an instruction should be issued. There were several scenarios in which the system assumed that assistance was needed: (1) if the agent was one street segment away from the destination to support destination recognition; (2) if the agent selected a costly detour towards the destination; (3) if the agent selected a branch that needed to be traversed back in case the shortest path was taken at the next junction. If none of these scenarios occurred, the agent followed the branch selected previously. The FCN system needed to be parametrized to define, among others, what a costly detour and the maximum allowed walking distance were. Depending on the city type, a different parametrization might be optimal. Therefore, different combinations were tested, and optimal parameters regarding a tradeoff between the success rate and the number of given instructions were found for each city.

The simulation results were promising for the FCN approach, as over 90% of the agents in every city were successful. Nevertheless, the TBT approach was more successful in guiding agents to the destination. Agents using the FCN approach received more turn instructions (normalized by the number of traversed junctions) than TBT agents. As expected, agents with low environmental spatial abilities were less successful with the FCN approach than agents with medium or high abilities. The results of this simulation and the potential to support spatial knowledge acquisition, as users are forced to engage with the environment, led to a real-world study with the FCN approach presented in the following article.

1.6.6 Free Choice Navigation in the Real World: Giving Back Freedom to Wayfinders

This article presented a real-world implementation of the Free Choice Navigation (FCN) approach presented in the previous article. It was compared with the widespread Turn-by-Turn (TBT) approach in a real-world wayfinding study to scrutinize whether own decisions and increased engagement with the environment while navigating lead to improved spatial knowledge acquisition (**RQ5**). As the FCN approach uses the environmental spatial abilities of the user, a series of online questionnaires had to be filled out before the in-situ experiment. The SBSOD questionnaire (see Section 1.5.3) was employed as a proxy of environmental spatial abilities. During this online session, participants were also asked about their willingness to walk longer routes (1) if they would gain more control over the walked route (compared to a fixed route) and (2) if they would gather more knowledge about the environment (**RQ6**). Besides comparing the novel FCN navigation approach, this study was the first application of the *Route Selection Framework* in a real-world study (see Section 1.6.1).

The in-situ wayfinding study took place on the outskirts of Vienna. All 48 participants (FCN - 26, TBT - 22) were unfamiliar with the experiment area. The study followed a between-subject design, i.e., each participant navigated either with FCN or TBT along one of the three similar routes selected with the assistance of the route selection framework. As a reminder, FCN participants received two pieces of information at the starting point: the direction towards the destination and the beeline distance to it. Later, at the upcoming junctions, the system decided whether a turn instruction, given via a Bluetooth earbud, was needed. If no instruction was issued, the participant decided which branch to follow. No graphical display was involved in the FCN approach (audio only). The TBT baseline was represented by the Android application *Organic Maps*, offering typical elements such as a map with a position indicator, including the facing direction. At the destination, participants were asked to complete questionnaires about subjective workload, user experience and usability. Afterward, they were given several tasks to approximate the acquired spatial knowledge about the environment they just traversed: pointing to the starting point, estimating the walked distance, drawing the traversed route abstractly, retracing the traversed route on a map and drawing in remembered points of interest (POI) on the same map.

All TBT participants reached the destination successfully, with a route no longer than 1.5 * shortest path length, whereas 23 out of 26 FCN participants were successful too. FCN participants received fewer instructions (normalized by the number of traversed junctions) than TBT users. Although FCN users were forced to make own decisions and to engage with the environment, none of the spatial knowledge acquisition tasks revealed a significant difference between both groups. It is, however, notable that FCN users achieved a high configuration similarity of the drawn POIs, although this group was not equipped with a map. Stimulation and novelty (UEQ) of the FCN system were rated higher than for TBT. No significant differences between both systems were found regarding SUS and NASA TLX. The two questions about willingness to walk longer distances (**RQ6**) revealed that acquiring knowledge about the environment is a stronger reason to walk longer routes than gaining control over the route. These answers showed people's interest in spatial knowledge acquisition.

1.6.7 BeeAR: Augmented Reality Beeline Navigation for Spatial Knowledge Acquisition

This article extended the study presented in the previous work (see Section 1.6.6). As the collected data showed, people are interested in gaining more knowledge about their environment. They are willing to walk longer routes to achieve this objective. On the other hand, the previous experiment demonstrated that making own decisions alone is not enough to foster spatial knowledge acquisition. As the Free Choice Navigation (FCN) approach does not provide information about the destination on a continuous basis and estimates the user's orientation, a novel system was proposed to overcome these shortcomings.

Beeline Augmented Reality (BeeAR) navigation is a head-mounted augmented reality system that displays the destination permanently in the real world. The user does not need to map any information between a device and the environment, as the digital information is anchored in the real world. The destination is marked with a magenta cuboid (width: 10 m; length: 10 m, height: 120 m). As this is the only information the navigation system provides, this navigation approach requires the user to make all decisions along the route. However, in contrast to the FCN approach, the user does not need to keep track of the destination, as it is permanently visible while looking toward it. This circumstance potentially frees up resources to engage more with the environment and possibly fosters spatial knowledge acquisition. In the previous study, data on three different routes were collected. For the BeeAR condition, however, data on only two routes (out of these three previously used routes) were collected due to time limitations. On each route, 8 participants navigated with the BeeAR approach. After the trial, the participants filled out questionnaires about workload, user experience, and usability. The tasks approximating the acquired spatial knowledge remained the same: pointing to the starting point, estimating the walked distance, drawing the traversed route abstractly, retracing the traversed route on a map and drawing in remembered points of interest (POI) on the same map.

For the analysis, there was data for three navigation approaches on two different routes (N = 48; FCN = 16; TBT = 16; BeeAR = 16). The data regarding TBT and FCN originated from the previous study described in Section 1.6.6. Given the same general conditions, this extension to the previous study also addressed **RQ5**. As the route/environment did not influence the results, data collected on both routes was analyzed together. FCN participants walked longer distances than TBT users. Five out of

16 FCN participants retraced their walked route perfectly on a map. The same applies to 14 TBT and 15 BeeAR participants. Especially the performance of the BeeAR group is notable, as all but one participant retraced the route perfectly, despite the absence of a map, in contrast to the TBT approach. BeeAR participants drew more existing points of interest (POI) on a map than FCN users. All three groups achieved a high configuration similarity, a measure that expresses the similarity between drawn POIs and their true locations.

1.7 Scientific Contribution

This subsection highlights the scientific contribution of this thesis. First, the potential influence of route selection on the results of wayfinding studies was scrutinized systematically. The results indicate that routes have the potential to invert study results. Therefore, route selection should be given more importance in the experimental design phase. Given that sample sizes may vary considerably in wayfinding studies, the potential influence of the sample size on the route's impact on study results was considered. The results indicate that the smaller the sample size, the more crucial route selection becomes. It has also been shown that the descriptions of selected routes are relatively poor, and even basic features are not reported. Given these problems with the current state of route selection for wayfinding studies, a route selection framework was developed to assist the researcher during this crucial phase of experimental design. The framework is flexible and can be adapted according to research needs (e.g., weighting system) and data availability. Furthermore, it leads to systematic and reproducible route selection. The framework can find *average-based* routes and also similar routes in other geographic areas. The first aspect should foster the generalizability of study results. The second aspect is a first step to facilitate the replication of wayfinding studies in other environments.

The second contribution block of this thesis is the analysis of the potential of free choices for spatial knowledge acquisition. Two novel navigation systems were proposed. Both navigation systems give wayfinders more freedom and encourage them to make own decisions while navigating. The first system, Free Choice Navigation (FCN), tries to balance the number of free choices, route length and the number of given instructions, whereas the second proposed navigation system, Beeline Augmented Reality (BeeAR), makes the destination permanently visible to the user. These two navigation approaches were compared with the widespread turn-by-turn approach (TBT) in a real-world user study. FCN participants did not perform significantly better than TBT users in tasks approximating the acquired spatial knowledge. BeeAR participants could retrace walked routes more accurately than FCN users, suggesting that making own decisions is not enough to foster spatial knowledge acquisition, as both systems require users, at least partially, to decide on their own. The main difference between both systems was that in the BeeAR condition the destination was permanently visible, whereas in FCN information about the destination was provided only at the beginning. On average, BeeAR participants remembered more details of the environment than FCN and TBT users. Although this difference was not statistically significant (Holm correction), it indicates that having an anchor point and making own decisions can benefit landmark knowledge. Nevertheless, participants of all three groups achieved a high configuration similarity between the drawn points of interest and their true locations, indicating that survey knowledge can also be acquired without an overview map and by traversing the environment only once. A further finding of the conducted experiment is that the TBT navigation approach does not affect negatively spatial knowledge acquisition in a pedestrian wayfinding scenario, as no significant differences between TBT and the other two proposed navigation systems were found in this respect. While planning the outlined user study, the above-mentioned route selection framework was employed for the first time in a real-world study.

Part 1 – Informed Route Selection for Wayfinding Experiments

Chapters 2 – 8 begin with information about the publication and the author's contribution to the corresponding article. Then, each chapter contains the reprint of the publication/submission. In total, there are six published articles and one submitted paper.

CHAPTER 2

Not Arbitrary, Systematic! Average-Based Route Selection for Navigation Experiments

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Not Arbitrary, Systematic! Average-Based Route Selection for Navigation Experiments

Bartosz Mazurkiewicz
TU Wien, Austria
bartosz.mazurkiewicz@geo.tuwien.ac.at

Markus Kattenbeck
TU Wien, Austria
markus.kattenbeck@geo.tuwien.ac.at

Peter Kiefer
ETH Zurich, Switzerland
pekiefer@ethz.ch

Ioannis Giannopoulos
TU Wien, Austria
igiannopoulos@geo.tuwien.ac.at

Abstract

While studies on human wayfinding have seen increasing interest, the criteria for the choice of the routes used in these studies have usually not received particular attention. This paper presents a methodological framework which aims at filling this gap. Based on a thorough literature review on route choice criteria, we present an approach that supports wayfinding researchers in finding a route whose characteristics are as similar as possible to the population of all considered routes with a predefined length in a particular area. We provide evidence for the viability of our approach by means of both, synthetic and real-world data. The proposed method allows wayfinding researchers to justify their route choice decisions, and it enhances replicability of studies on human wayfinding. Furthermore, it allows to find similar routes in different geographical areas.

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1 Introduction

Selecting a route for a human wayfinding study in a systematic manner is a non-trivial task. Despite its potential impact on the results, reasonable justifications for routes based on their features are often neglected. In this paper, we propose, implement and evaluate a methodological framework which enables researchers to choose a route for human wayfinding experiments in a given area according to predefined, weighted criteria. The determined routes are – with respect to these criteria – representative for a (weighted) average route for the chosen area. Using this framework will, therefore, lead, among others, to an increased comparability and replicability of in-situ wayfinding studies.

Starting with the replication crisis in psychology [34], reproducibility and replicability have both seen increased interest in all subfields of geographical sciences in recent years (see e.g., [32, 35, 20, 24]). At the same time, studies which aim to understand human wayfinding and/or how interactive assistance can be provided to wayfinders have gained momentum [21, 12]. These research efforts will likely be continued in the future, as there is neither a

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general agreement on algorithms nor route descriptions or an anywhere close to definite understanding of the interplay between spatial cognition and the assistance provided by mobile navigation companions. While there has been some recent progress in terms of reproducibility (i.e., software and data are made available to the scientific community and rerunning the analysis using the software and data yields the published results, see [6]), e.g., through initiatives like the AGILE initiative on reproducible publications (see also [32]), increasing the level of replicability may be much harder to achieve. In particular, up until now, the replicability of wayfinding studies often suffers from the possibility to choose a route in a systematic manner: the decisions which led to the choice of a particular route are often not made explicit, leading to the impression that routes are often chosen in an ad-hoc manner (see Section 2). As a result, oftentimes information other than length, number of decision points, and a rough classification of the urban environment (e.g., European) is not given. As a consequence, the impact of differences in route properties cannot be assessed in an appropriate manner if researchers fail to replicate the results.

2 Related Work

This section provides a thorough overview of route features in studies involving wayfinding tasks. It provides the basis for the set of features, we use in our methodological framework. (see Section 3). In order to gain an insight into common practice among researchers to justify their route choices and the route characteristics they pay attention to, we have systematically screened six major venues (conferences and journals) in the broader area of geographic information science and related fields since 2010.

While our search is not exhaustive by any means, the number of papers screened is still suitable to provide a reasonably grounded insight into the state-of-the-art. In identifying relevant papers, we focused exclusively on studies involving either wayfinding tasks by participants or studies, in which routes were presented to users, e.g., on maps. This implies, that we deliberately excluded all studies involving route retrieval from memory without performing an actual wayfinding task or which involved human wayfinding without predefined routes.

Overall, 32 papers were found which present studies on wayfinding/navigation in both, virtual and real-world environments. Each of the relevant articles/papers found was checked for the rationale researchers have given for the chosen route and which route characteristics they have mentioned explicitly.

Table 1 reveals several important insights regarding common practices among researchers: The three most often named aspects are: the length of a route (mentioned by 16 publications), the type (e.g., a residential area) of environment a study was conducted in (15), and the name of the city/town of a study (11). While these criteria are the most frequent ones, it is important to note that only half of the papers mention route length and type of environment whereas the name of the city/town is stated only by one third of the papers explicitly. In addition to basic route data and information about the local environment of different granularity, a variety of features mentioned by researchers deal with decision points (DPs). We consider each intersection on a route as a decision point, which is neither the start nor the end point of the route. While authors describe at least the overall number of DPs and the proportion of those DPs which require a turn, the layout of the DPs is given rather rarely. Several other aspects related to route instructions, visibility of environmental cues and – in case two or more routes are compared – how routes relate to one another are mentioned occasionally.

Table 1 Overview of route features named (multiple features per paper possible) in human wayfinding studies in major research outlets since 2010. Relevant papers for the AGILE conference: [1, 14, 23]; for the GIScience conference: [38, 29, 19]; for the COSIT conference: [40, 46, 47, 18, 22, 11, 3, 2]; for the IJGIS: [26]; for the LBS Journal: [13, 37, 39]) and for the SCC Journal: [33, 45, 49, 27, 36, 17, 43, 25, 48, 42, 16, 7, 31, 44].

	Feature	AGILE	COSIT	GIScience	IJGIS	LBS	SCC	Freq (N=32)
Basic Route Data	length	3	4	1	1	2	5	16
	walking duration	0	2	2	0	0	0	4
	name of city	1	4	0	0	2	4	11
	size of area	0	0	0	0	0	1	1
Local Environment	uniformity of env.	0	1	0	0	0	0	1
	type of env. (e.g., residential)	1	2	1	0	2	9	15
	terrain (e.g., flat)	0	1	0	0	0	0	1
	complexity of env. (e.g., narrow streets)	0	4	0	0	1	3	8
	type of walkways (e.g., sidewalk)	0	0	1	0	1	0	2
Decision Point / Intersection	#DP	1	1	1	0	0	3	6
	#DP with turn	2	1	0	0	2	3	8
	#type of turn (l,r, non-turn)	1	0	0	1	0	0	2
	Inclusion of diff. actions at DP	1	0	1	0	0	0	2
	DP layout (e.g., 3-way, 4-way) described	1	1	0	0	0	1	3
	variety of DP layouts mentioned	0	0	2	0	2	0	4
	DP density	0	0	0	0	1	0	1
	Distance between DP	0	1	0	0	0	0	1
Route Instruction Features	inclusion of landmarks	0	0	1	0	1	4	6
	inclusion of street names	0	0	1	0	0	0	1
	Destination (landmark)	1	0	0	0	0	0	1
View / Visibility related	views offered (e.g., open vista)	0	0	1	0	0	0	1
	visibility of dest. from start (or vice versa)	0	1	0	0	0	1	2
	long-distance vistas	0	1	0	0	0	1	2
	visibility of street names	0	0	0	0	0	1	1
Relation to other Routes	equal length	0	0	0	0	0	1	1
	equal starting and end points	0	0	0	0	0	1	1
Number of distinct criteria		9	13	10	2	9	14	26

Taken together, this overview of common practices provides evidence for a lack of proper justification of route choices and only very basic features of routes being made explicit. In particular, half of the publications do not even mention basic properties, such as route length, and even environmental and decision point-related aspects are insufficiently described. This is, from our perspective, a clear barrier to any attempts to the replicability of these research results.

3 Route Selection Criteria

It is obvious that route selection is deeply intertwined with a study's research question. The literature review above has revealed, however, that this selection is often insufficiently justified. Moreover, even basic route properties are often not made explicit. This may be a hint to the practice to use ad-hoc choices for routes, a decision which may result in a considerable bias stemming from route choice. Even for those studies, which want to assess the impact of a given route, it would be desirable to be able to quantify the degree as to which a chosen route represents a special case given a set of criteria researchers want to take into account. The possibility to select routes for human wayfinding studies in a systematic and reproducible manner is, therefore, highly desirable. In order to achieve scientifically valid results, researchers interested in conducting (not only replicating) human wayfinding studies must base their research on a route, which is selected in a systematic and reproducible manner. For many of these studies, it is desirable not to use a route which would represent a special case given the researcher's requirements about routes. In human wayfinding studies in real-world, the population of routes to select from encompasses millions of possible routes of a given number of decision points for any area of non-trivial size. Given these figures, selecting a route based on the average of all routes fulfilling the researchers' requirements seems reasonable for those studies which do not use a route as an independent variable. Outliers are expected to have only a small effect as the population is vast, and the number of criteria to be taken into account is large. Therefore, the best possible route to be chosen would be a route, which meets the average for all criteria a researcher wants to take into account as close as possible. We refer to such a route using the expression *average route* because it is average-based. As mentioned above, even those studies in which route is an independent variable, knowing the deviation from the average route in an area may provide researchers with valuable information to interpret their results.

In order to make research more comparable and to provide other stakeholders (scientists, urban planners, politicians etc.) with assistance to choose one route for their needs, we present an approach which finds a route which is as close as possible to a theoretically existing average route in a given area. The idea is that a route selected in such a systematic manner should provide more transferable results as it reflects the characteristics of the specified area.

Based on the set of criteria currently used by researchers (see Section 2) our framework takes the following criteria into account. We base the decision made for in-/exclusion on both, prior research practice and the widespread availability of data:

Pre-emptive criteria

Researchers must select, first and foremost, an area in which they want to conduct their study in. In accordance with the widespread report of this criterion, we use the number of decision points (DPs) as a criterion researchers must specify. If researchers wish to do so, they can additionally provide a minimum and maximum route length.

Used criteria

According to the literature reviewed, researchers consider criteria related to DPs as important. Therefore, our framework considers the *average number of options a DP* offers and the *number of n-way intersections* on a route – both of which are derived from the intersection framework [10]. The same framework [10] provides information about the *regularity of a DP* (the sum of angles branches need to be rotated in order to create a regular intersection, see [10, p. 3:4] for further details). As a fourth DP-related aspect, we consider the *number of right, left and non-turns* at DPs on a route. We calculate these properties according to the point orientation algorithm [4]. In order to count non-turns and avoid false negatives we use a 10 degree threshold, i.e., a 20 degree cone, to identify continuations. Undoubtedly, landmarks play an important role in human navigation. However, we lack sources of salience values for arbitrary regions. Consequently, we use points of interest (POI) as a proxy (see e.g., [9] or [41] for publications with a similar approach). As there is no commonly agreed definition of POI available, we extract POIs from OpenStreetMap data based on tag `amenity=*`. Our methodological framework, however, is open to other definitions researchers may want to employ. We take two POI-related criteria into account: *the average number of POIs at a DP* and the *uniqueness of a POI category at a DP*. The average number of POIs on a route is given by the amount of POIs within a given radius from any DP divided by the number of DPs. The uniqueness of a POI, according to Rousell and Zipf [41], is defined as $\frac{1}{j}$ where j is the number of POIs of the same type (e.g. restaurant) in the considered set. Finally, two environmental features are considered: *Slope* (shares of route with negative, positive and zero slope sourced from a digital elevation model[1]) is taken into account as a proxy for criterion terrain, whereas land cover data (Urban Atlas[2]) reflect the *type of environment*.

[1] `https://www.wien.gv.at/ma41datenviewer/public/`, last access June 5th, 2020
[2] `https://land.copernicus.eu/local/urban-atlas/urban-atlas-2012`, last access March 20th, 2020

This list can be extended if more data is available or of particular interest for a navigation study to be conducted. In short, we are aiming to get as close as possible to the average route based on user-defined weights for route features in a given area.

4 Methodology

Given a certain area in a built environment, we aim at ranking all possible routes with a given number of DPs. This ranking is based on the average of all routes in this area according to a set of given criteria (see Section 3). The closer a route is to the average values, the higher this route will be ranked. In the following we provide a step-by-step description of the required computation steps. At the end of this section information about software and hardware used is provided. Our street network data are based on OpenStreetMap. The computations are based on a graph created out of nodes representing intersections and edges representing the street segments. For a detailed description of all data sources see Section 3.

Step 1: Extracting all potential routes. We represent *all* potential routes[3] in the given area with their criteria as a decision matrix $\boldsymbol{X'}$. As these criteria are measured on different scales, a z-score standardization is applied in order to normalize the values, i.e., a z-score of $z = 0$ represents the average. Since we are interested only in the deviation from the average, $\boldsymbol{X'}$ contains only absolute values of z-scores.

$$X' = \begin{bmatrix} x'_{11} & x'_{12} & \dots & x'_{1m} \\ x'_{21} & x'_{22} & \dots & x'_{2m} \\ \dots & \dots & \dots & \dots \\ x'_{n1} & x'_{n2} & \dots & x'_{nm} \end{bmatrix} \tag{1}$$

where n denotes the number of routes and m the number of criteria. In order to retrieve all possible routes of a certain number of DPs without loops, a street network graph was utilized. This can be approached as a subgraph isomorphism problem, which is NP-Complete. Although street networks can be modeled as planar graphs (for simplification reasons) in reality they are not [5]. Thus, the subgraph isomorphism problem on non planar graphs grows in general, exponentially. However, there are algorithms with acceptable practical execution time[8].

Step 2: Best possible solution. Based on the z-scores for all criteria, we retrieve the *best possible solution* A^+ (see Eq. 2): This is an artificial (and unlikely to exist) route which comprises the minima of all z-scores, i.e., it is as close to the average of all criteria one can get.

$$A^+ = (y_1^+, y_2^+, \dots, y_m^+) \qquad where \quad y_j^+ = \min_{i=1,2,\dots,n} x'_{ij} \tag{2}$$

The best possible solution contains the minimum for each criterion. A value of 0 means that this value reflects the global mean perfectly. Negative values are not possible due to the performed standardization step.

[3] It is important to note that users of the proposed method are free to take any type of routes into account,i.e. routes w/o loops, shortest path between two distinct points, round tours etc.

Step 3: Weighted similarity. There are several spatial as well as spatio-temporal similarity measures available for a variety of problems [15, 30]. We identified the cosine similarity and the weighted euclidean distance as the most promising ones for our approach. The cosine similarity measure, which is widely used for multidimensional data, had to be discarded after encountering counter-intuitive results during testing. The explanation for this discrepancy between intuition and hard numbers is that cosine similarity measures only the angle between two normalized vectors, and therefore ignores the magnitude of difference between them.

As described earlier (see Section 3), researchers can specify weights for each criterion according to their research interest (i.e., the higher a weight, the more important an average value of a characteristic is to a researcher). These weights are used during the distance calculation between a route and the best possible solution. Each route is compared to the best possible solution (equation 2) by means of the n-dimensional weighted euclidean distance: In Equation 3, x'_j represents the j-th criterion of a route and w_j is the weight for this high-level criterion.

$$dist = \sqrt{\sum_{j=1}^{m} w_j (x'_j - y_j^+)^2} \tag{3}$$

A high-level criterion is, for example, the regularity of a decision point which can be represented by the sum of angles needed to obtain a regular intersection [10]. It is, however, not reasonable to build averages across different n-way intersections. Therefore, the sum of angles is computed for each n-way intersection (called subdimension) separately. For example: If seven is the largest number of branches for all intersections in the area-of-interest, the sum of angles is calculated for 3- to 7-way intersections separately. In this particular example each subdimension would have a weight of $w_j/5$, where w_j is the weight assigned to criterion *decision point regularity*. The sum of the weight vector is 1.

Step 4: Ranking of results. Finally, all routes are ranked according to their distance (equation 3) to the best possible solution (equation 2). The smaller the distance, the closer a route is to the average in the area of interest, given the user defined weights for the applied criteria.

Implementation. This paragraph specifies the software and hardware used to implement our approach. In order to find all possible routes without loops (step 1) SageMath 9.0 with its SubgraphSearch function[4] was used, whereas steps 2-4 were implemented in Python 3.6. Two features from the real world example (see section 5.2), namely, the *average number of POIs per DP* and *type of environment* were calculated in a PostGIS (v 2.4) database. All analyses run on an AMD Ryzen Threadripper 1950X 16-Core Processor, 3400 Mhz, with 64 GB RAM.

5 Evaluation

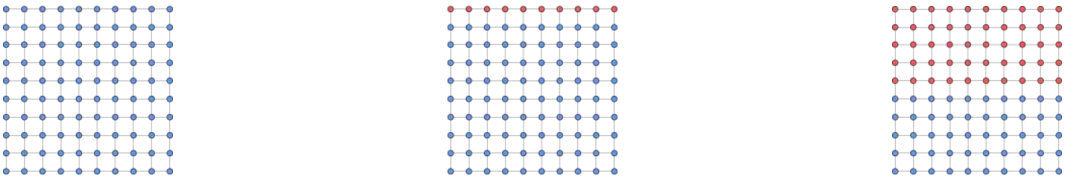
As a proof of concept, we first evaluate our approach on synthetic data (subsection 5.1). Using synthetic data enables us to use predefined values for all criteria and, thereby, formulate the expected results. We then continue with a real-world example in Vienna, Austria (see subsection 5.2).

[4] `http://sage-doc.sis.uta.fi/reference/graphs/sage/graphs/generic_graph_pyx.html#sage.graphs.generic_graph_pyx.SubgraphSearch`, last access June 5th, 2020

5.1 Synthetic data

We use 100 x 100 regular grid graphs as synthetic data. The graph used has 10 000 nodes and 19 800 edges. All edges have the same length and characteristics (which is a difference to the real-world data, see Section 5.2). We distinguish between type I and type II nodes. While type I nodes have 3 POIs all of which have unique categories, type II nodes have 6 POIs which show an average uniqueness of their categories of 1/3. Therefore, routes will have different average POI numbers due to different proportions of type I and II nodes in a route. They have different characteristics regarding POIs in order to be able to observe changes in results. It is important to note that the order of magnitude of these differences does not matter as long as it is unequal to 0. The 4 corners of the grid have only 2 edges and are considered as "2-way intersections": Taking them into account is reasonable to show that our approach takes the global distribution (frequency) of n-way intersections into account. All nodes along the border of the graph, with exception of the 4 corners points just mentioned, have 3 edges. All other nodes have 4 edges, i.e., they are regular 4-way intersections.

For all evaluations on synthetic data we set the number of decision points to $k = 7$. This number was chosen due to computation time limitations, which is reasonable based on the fact that the route recommendation algorithm is NP-Complete (due to the subgraph search problem). Based on all these routes the best possible route was calculated (see equation 2) as target route. In total, 55 396 400 possible routes without loops (represented as subgraphs) having 7 DPs plus 1 starting and 1 end point were found in this synthetic graph. These routes do not have to be a shortest path between two points. Routes have, in general, the same characteristics (e.g., slope) but they vary considering with respect to the type of actions taken at decision points (i.e., turning right or left and continuations).



(a) **(b)** **(c)**

Figure 1 Schematic Representation of Synthetic Data (data used were 10 times bigger, but with the same ratios of type I (blue) and type II (red) nodes): (a) Scenario 1: Regular grid network with only nodes of type I; (b) Scenario 2: Regular grid network with ratio 9:1 of type I to type II nodes; (c) Scenario 3: Regular grid network with equal shares of type I to type II nodes.

We evaluate our approach with respect to synthetic data based on three scenarios, which differ in the proportion of type I and II nodes (see Figure 1). Each of the scenarios share three high-level criteria, namely the number of 2-, 3-, 4-way intersections, the sum of angles needed to obtain regular 3- and 4-way intersections [10] and the frequency of right and left turns and non-turns at decision points.

Scenario 1

In this scenario the whole 100 x 100 regular grid network consists of type I nodes, only (see Figure 1a). 97% of all possible routes contain 4-way intersections only and all of these are regular 4-way intersections. The average number of right-, left- and non-turns is 2.18, 2.18 and 2.64, respectively. Based on these figures we expect the route with the least distance to the average route to have 4-way intersections only, 2 right, 2 left and 3 non-turns at DPs. As all intersections are regular, the sum of angles equals zero and, therefore, is omitted in the results for synthetic data.

Table 2 presents the results. Due to the synthetic dataset, we observe many routes having equal scores. Therefore, the table reports the first 10 groups of routes, where each group represents a unique combination of the two high-level criteria (number of n-way intersections and frequency of right and left turns and non-turns). The results meet our expectations, as rank 1 group contains routes which comprise 4-way intersections only and show 2 right and left turns and 3 non-turns at DPs. While lower ranks in the table show the same distribution of intersections, rank 1 routes are the ones with the least euclidean distance to the best possible route. It is important to note that the euclidean distance reflects different degrees of deviations from the best possible route: The worst group, which is not shown in Table 2 consists of routes which have one 2-way and six 3-way intersections, 1 left or right and 6 non-turns. Similarly (also not presented in Table 2 for space reasons), routes with the same distribution (0,0,7) but with no left/right turns and 7 non-turns got a lower rank than routes with n-way distribution 0, 1, 6 and a more balanced distribution of actions at decision points.

Table 2 Results for scenario 1 where all nodes are of type I. Only the first 10 highest ranked groups of routes are shown in the table, some of which share a rank.

Rank	# Routes	# Intersections			# Turns		
		2-way	3-way	4-way	left	straight	right
1	7 635 056	0	0	7	2	3	2
2	6 341 188	0	0	7	2	2	3
	6 341 188				3	2	2
3	3 931 208	0	0	7	1	3	3
	3 931 208				3	3	1
4	3 808 196	0	0	7	1	4	2
	3 808 196				2	4	1
5	3 869 072	0	0	7	3	1	3
6	1 458 408	0	0	7	1	2	4
	1 458 408				4	2	1

Scenario 2

In scenario 2 the grid network now contains type I and type II nodes at a ratio of 9:1 (see Figure 1b). This induces variance in the data by including points-of-interest (POIs) as an additional high-level criterion, which comprises the number of POIs and the average uniqueness of a POI at a DP. Again, all high-level criteria are equally weighted. As no changes to the layout of the graph were applied, we expect routes with exclusively 4-way intersections to be higher ranked than those including also other types of intersections. In contrast to scenario 1, however, routes can now have a different number of type I and II nodes: As the average number of POIs per DP in all routes is 3.26 and the average uniqueness of POIs per DP equals 0.94, we expect routes with six type I nodes and one type II node to be higher ranked than other combinations of those types[5].

[5] This assumption is also backed up by the average number of type II nodes in a route which equals 0.61.

Table 3 Results for scenario 2. Only the first 11 highest ranked groups of routes are shown in the table, some of which share a rank. POI subdimensions are rounded to 2 decimals.

Rank	# Routes	# Intersections			# Turns			# Type II Nodes	Avg. # of POIs	Avg. Uniq. of POIs
		2-way	3-way	4-way	left	straight	right			
1	31 024	0	0	7	2	3	2	1	3.43	0.90
2	6 914 264	0	0	7	2	3	2	0	3	1
3	23 934	0	0	7	2	2	3	1	3.43	0.90
	23 934				3	2	2	1	3.43	0.90
4	5 743 264	0	0	7	2	2	3	0	3	1
	5 743 264				3	2	2	0	3	1
5	38 668	0	0	7	2	3	2	2	3.86	0.81
6	32 526	0	0	7	2	2	3	2	3.86	0.81
	32 526	0	0	7	3	2	2	2	3.86	0.81
7	14 160	0	0	7	3	3	1	1	3.43	0.90
	14 160				1	3	1	1	3.43	0.90

The results presented in Table 3 meet our assumptions. The highest ranked group represents routes which have only 4-way intersections, a balanced (close to global average) frequency going right, left or straight ahead at a decision point throughout the route, one type II node and the closest possible values to the global average regarding POI subdimensions.

Scenario 3

In scenario 3 we increase the variance in the data by changing the proportion of type I to type II nodes to 1:1, while keeping the graph layout unchanged (see Figure 1c). This means, scenario 3 simulates an area in which two 2 subareas are clearly different but have an equal share. The same high-level criteria as in scenario 2 are applied. As the frequency of n-way intersections and direction changes remain unchanged, we still expect routes with 4-way intersections only and a balanced frequency of right-, left- and non-turns at a decision point to be higher ranked. Given the 1:1 ratio of node types and the odd number of decision points (7), we expect routes with either three type I and four type II or four type I and three type II nodes to be ranked highest. These two combinations of type I and type II nodes are equally close to the global average for both POI subdimensions (avg. number POI: 4.5, avg. uniqueness POI: 0.66). The results for the third scenario are presented in table 4. In-line with our expectations, the highest ranked group has only 4-way intersections, a balanced (close to global average) frequency of (non-)turns and a balanced ratio between type I and type II nodes and, therefore, close to global average values for both POI subdimensions.

Taken together, the results of these three scenarios provide evidence that our approach yields reasonable results based on the controlled conditions of synthetic data. We will now continue with real-world data and the full set of criteria mentioned before (see Section 3).

5.2 Real World Example

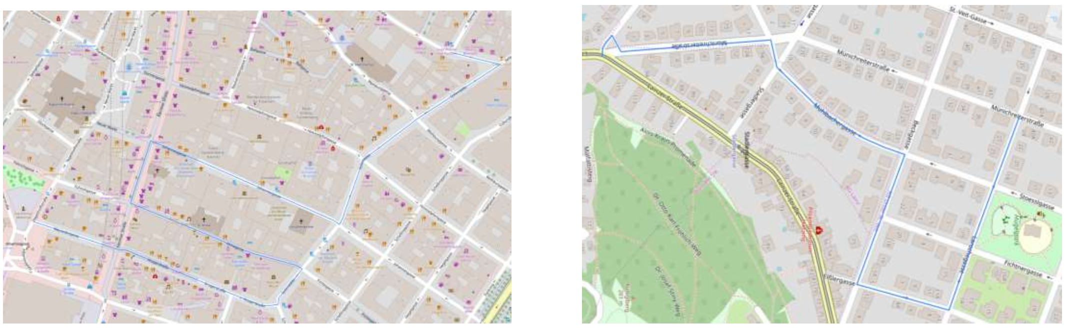
We have chosen two different areas in Vienna, Austria. Both regions significantly differ with respect to their degree of sealed soil, where Region 1 (located in the city center) shows a high degree and Region 2 (residential area) a low-medium degree of soil sealing (according to Urban Atlas 2012). We specified both pre-emptive criteria (see Section 3) and set the number of DPs to $k = 10$, and route length to a range between 1 000 m and 1 500 m. The length of possible routes in terms of both, the number of DPs and the distance, was chosen

Table 4 Results for scenario 3. Only the first 8 highest ranked groups of routes are shown in the table, some of which share a rank. POI subdimensions are rounded to 2 decimals.

Rank	# Routes	# Intersections			# Turns			# Type II Nodes	Avg. # of POIs	Avg. Uniq. of POIs
		2-way	3-way	4-way	left	straight	right			
1	37 092	0	0	7	2	3	2	3	4.29	0.71
	37 092				2	3	2	4	4.71	0.62
2	38 668	0	0	7	2	3	2	2	3.86	0.81
	38 668				2	3	2	5	5.14	0.52
3	28 310	0	0	7	2	2	3	3	4.29	0.71
	28 310				3	2	2	3	4.29	0.71
	28 310				2	2	3	4	4.71	0.62
	28 310				3	2	2	4	4.71	0.62

based on computation time (see Section 5.1). The underlying graph for Region 1 has 1 196 nodes, 1 740 edges and 4 290 636 possible routes of 12 points length (10 decision points plus start and end point which are not considered to be DPs). Of these routes, 62 294 have a length between 1 000 m and 1 500 m. The underlying graph for Region 2 has 498 nodes, 744 edges and 2 276 070 possible routes of 12 points length and 834 114 of these have a length between 1 000 m and 1 500 m. The observed difference in the number of considered routes is likely a result of the fact that the average segment length between two subsequent DPs in the city center area (Region 1, 2.25 km^2 area) is less than in case of the residential area (Region 2, 2.84 km^2 area).

For each region the closest to average route was calculated regarding the following 6 high-level and equally weighted criteria: *cardinality of decision points* (the number of n-way intersections on a route and the derived average options per DP), *frequency of right/left and non-turns*, *terrain* (proportion of negative, positive and zero slope), *POIs* (average number within a 10 meter radius and average uniqueness of category per DP), *regularity of DPs* and *type of environment* (land cover data). Figure 2 shows the routes for both regions which are closest to the best possible solution. Considering the above-mentioned criteria, routes from A to B achieve the same score as those from B to A. They only differ symmetrically in *slope* and *frequency of right/left and non-turns*. This symmetry causes an equal distance to the best possible route. Non symmetrical attributes like directed viewsheds would lead to a difference in score between route A to B and route B to A.



(a) **(b)**

Figure 2 The closest to average routes for Region 1 (a) and Region 2 (b) considering all criteria mentioned above (see Sec 3), which were equally weighted.

Table 5 Comparison between highest ranked routes and the best possible solution. Land cover classes are Urban Atlas classes: A (11100), B (11210), C (11220), D (11230), E (12100), F (12220), G (12230), H (14100) and I (14200). Land cover values do not sum up to 1 due to rounding. If there are two numbers for a feature this is due to having 2 winners for a region. Why the number of turns of best possible routes do not sum up to 10 is explained in the discussion.

Name	Avg. Options	# Intersec.				# Turns			Slope			Avg. # of POIs	Avg. Uniq. of POIs	Regularity				Land Cover %								
		3	4	5	6	l	s	r	neg	none	pos			3	4	5	6	A	B	C	D	E	F	G	H	I
Win. Reg 1	3.7	3	7	0	0	4/4	2	4/4	.05/0	.95	.05/0	.2	.2	55.68	16.31	NaN	NaN	.57	0	0	0	.09	.34	0	0	0
Best Reg 1	3.7	3	7	0	0	4	3	4	.03	.94	.03	.3	.17	51.97	17.24	83.2	69.34	.54	0	0	0	.09	.36	0	.01	0
Win. Reg 2	3.9	3	5	2	0	3/4	3	4/3	.03/.06	.91	.06/.03	0	0	57.75	19.86	72.80	NaN	0	.09	.48	.07	0	.36	0	0	0
Best Reg 2	3.9	3	5	2	0	3	3	3	.08	.84	.08	0	0	58.98	18.30	72.59	148.46	0	.06	.44	.07	0	.36	.01	.03	.01

Table 5 presents numerical results by providing figures for both, the highest ranked routes (will be referred to as *winners*) and the best possible solution, i.e., a hypothetical route which shows closest to average values for all criteria (will be referred to as *best*). Two aspects are important to be kept in mind: 1) The best possible solution does not need to be an actually existing route (see Sec 6); 2) there are two winners per region as each route can be traversed in both directions.

For both regions, the distribution of scores (i.e., the euclidean distance to the best possible solution) is similar (see discussion for an explanation of the maxima). The quantiles for the score in Region 1 are 0%: 0.2250, 25%: 0.5894, 50%: 0.7290, 75%: 0.8569 and 100%: 32.3001. The score quantiles in Region 2 are 0%: 0.1738, 25%: 0.5198, 50%: 0.6468, 75%: 0.8875, 100%: 5.2246. Regarding the *cardinality of DPs*, both winners in each region show a perfect match with best, respectively. With respect to *slope*, winners 1 are closer to best 1 than winners 2 are to best 2. It is vice versa regarding *POIs*, in which case winners 2 match best 2 perfectly (generally speaking, Region 2 is an area which is poor in POIs), whereas winners 1 have, on average, slightly less POIs at a DP than the best possible solution, but their uniqueness is higher. Looking at the *regularity of DPs* both routes reflect global averages very well if and only if they have this kind of n-way intersection[6]. Regarding *land cover* the differences between winners and best in both regions are minimal[7]. Regarding *frequency of right/left and non-turns* winners in Region 1 show one continuation less than the winner, whereas winners in Region 2 show either one left or right more than the best possible route. In both cases, the frequency of the best possible route is impossible to achieve (see Sec 6 below). Taken together, both winners in each region come close to the best possible route – which is hypothetical in this case and very unlikely to exist in general but reflects global averages as good as possible.

6 Discussion

In this work we propose and evaluate a systematic approach for the selection of pedestrian routes in a street network, with a focus on wayfinding experiments. As described in the related work section, a proper selection of street routes is crucial for several types of empirical studies. Such a systematic approach can help select a route based on a multitude of criteria and, furthermore, reduce the time necessary for manual selection. Moreover, the proposed approach can be seen as a step towards replicability of research, allowing to select a similar route at a completely different geographic location by exchanging the best possible solution

[6] NaN in a route are not contributing to the euclidean distance.
[7] If land cover does not sum up to 1 this is due to rounding.

with the target route of another location. The proposed approach was evaluated utilizing synthetic data serving as a ground truth. The results of this evaluation confirmed the validity and applicability of our approach. We performed a proof of concept evaluation using real data, once taken from the city center and once from a residential area in Vienna, Austria.

Two aspects of the results achieved for the real-world data need to be discussed in more detail: Firstly, the difference in distance between the the upper quartile and the maximum is very large for Region 1. However, the two routes (out of 62 294) having scores above 32 both have a 6-way intersection – a feature which is very uncommon for Region 1. Obviously, Region 2 has no large outliers as the maximum euclidean distance is far less than for Region 1. For both regions, however, the distances up to the upper quartile are numerically small; it is, therefore, a matter of future research whether these differences are meaningful for wayfinding research and with respect to which criteria this might be the case (see Section 7). Secondly, the fact that the best possible solutions do not match the predefined number of DPs by one needs in-depth discussion. All best possible solutions are calculated based on a z-score, which depends on the population mean and standard deviation. Due to the size of the population of possible routes, it is very unlikely that mean and standard deviations both are integers. The number of right, left and non-turns on an actual route (which is the third factor needed to calculate a z-score), however, must be integers. The figures need to be rounded (i.e., either floored or ceiled depending on the decimal digits), accordingly. In addition to that, the means of right and left turns must be symmetric. Hence, the best possible solution as a hypothetical route can show this anomaly of more/less (± 1) DPs than actually requested, whereas all actual routes in the population always have the predefined number of decision points (and turns). It is important to note that, although slope is a symmetric feature as well, its value can be decimal. Moreover, all other criteria are invariant to the direction of travel on a route. To conclude, our framework supports systematic and deterministic route selection for experiments considering weighted features provided by the researcher. Furthermore, exchanging the best possible solution with another target route (using this route as the average one) allows to find a similar route in a different place of the world.

The criteria utilized in this work served as an example and can be easily extended or even replaced by others. Of course, the more criteria used, the longer the route in terms of DPs, or the larger the search area, the more computation time will be required. In most cases, however, finding a reasonable route at the city level should be sufficient and this should be possible in less than one day of computing time as our results were. Our methodological framework allows to extend the list of criteria taken into account. Several aspects come to mind: the segment length and orientation might be worthwhile to be taken into account; if doing so, the number of POIs per segment of a given length may be worthwhile to take into consideration in order to study on-route landmarks (see [28]). Traffic data, flow of humans in an area and noise (e.g., stemming from factories) may have an impact on in-situ studies and might be considered, although it might be very difficult to obtain this type of data on a large-scale basis. While DPs per se have been extensively considered already, the order of turns (e.g., llrrslr) and the sequence of intersection types might be included (see e.g., [12]). One particularly important environmental feature, which is also missing due to unavailability of large-scale data, is the architectural style/diversity of buildings in a given area.

Computation time and difficulty of validating the results obtained from real data are the main limitations of this work. Concerning computation time, although this approach cannot be utilized for real-time purposes, most of the relevant cases for wayfinding will not be affected by that. Nevertheless, reducing computation time based on existing sub-graph search algorithms is already feasible (see Section 4), although this is out of the scope of our work. Results for real data are difficult, if not impossible, to validate. Synthetic data approaches for validation like the one presented above, however, ensure the validity of the results at least for the cases covered.

7 Conclusion and Outlook

The proposed approach can be considered as a valuable methodological framework, which can help to make informed decisions concerning route selections. As a consequence, this framework can partially support the design of experiments and enhance replicability.

The results of the presented approach strongly rely on the availability of appropriate data sources. The availability of pre-computed data, such as DP type and regularity [10] are crucial for lowering the required computational costs. As a consequence, we will follow the path of open data and pre-compute several features that might be relevant for route selection. Furthermore, we plan to provide an API[8] that will ease the access to our framework and allow to compute a winner route with minimal effort.

Although for most cases only the best result (i.e., the winner route) is relevant, there might be cases were the comparison between routes is of interest. Therefore, it is reasonable to study whether the Euclidean distance is actually justifiable by means of empirical results: The distance metric chosen should reflect empirical results, i.e., if participants are subject to routes which differ more, less comparable results should occur and vice versa. We are going to conduct within-group design wayfinding studies on this problem.

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CHAPTER 3

Route Selection - From Replication to Recreation

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Author's Contribution: conceptualization, methodology, software, formal analysis, investigation, data curation, writing — original draft preparation, writing — review and editing, visualization

Route Selection - From Replication to Recreation

BARTOSZ MAZURKIEWICZ, TU Wien, Austria
IOANNIS GIANNOPOULOS, TU Wien, Austria

The choice of a route from an origin to a destination depends on several criteria. These criteria can range from route length to environment type. In several situations, we are not only interested in finding a route between two points, but to find a route between all possible origin-destination points in a specific geographic area. This is very common during experimental design, when one is seeking for a generalizable route to evaluate a navigation system. For this case, the selected route should be representative for the area, and not an exception with peculiarities. In this work we demonstrate (1) how to choose an *average* route for a bike navigation study in Vienna, Austria and (2) how to find similar routes in Florence, Italy and Bremen, Germany in order to replicate the study. The selection is based on route features and associated weights. They can be highly customized according to the needs. We demonstrate our approach and introduce four application scenarios to exemplify the benefits of a systematic route selection.

CCS Concepts: • **Information systems** → *Geographic information systems*; *Location based services*; *Decision support systems*; • **General and reference** → *Empirical studies.*

Additional Key Words and Phrases: Route Selection, Similar Routes, Human Wayfinding, Navigation, Experiments, Replicability

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1 INTRODUCTION

Navigation systems have found their way in our daily lives and are used in order to navigate us while walking, driving by car or even by bicycle. There are many possible routes between an origin and a destination and these can have different properties, such as total length and number of intersections, amongst other. Navigation systems, utilize these properties in order to compute a desired result, e.g., shortest or cognitively easiest route. Navigation systems are evaluated in order to prevent undesired effects, such as user frustration, but also for the investigation of novel systems. Researchers strive to design their experiments as valid and replicable as possible. The route selection is one of the most important steps towards these experimental goals. Unfortunately, this selection is mostly performed by the rule of thumb, trying to mix different types of street segments and intersections.

Mazurkiewicz et al. [4] introduced a framework that is able to rank routes based on given criteria, such as length, number of intersections, slope and number of turns, amongst other. This ranking is based on the average route of the considered area. For instance, the highest ranked route will be the most representative/average route in the given environment fulfilling the given weighted criteria. This is the first systematic approach towards route selection for experimental design. The route selection is rather a universal problem and relevant for pedestrians, cyclists [5] and cars. There have been some approaches trying to tackle this problem. Spretke et al. [6] derive representative driving

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routes for cars based on car fleet trajectory data. Unfortunately, the data is not always available, either in the necessary amount or at all.

Through such a systematic approach [4], a novel bike navigation system can be evaluated on routes resembling other routes in the given area without introducing peculiarities (e.g. 8-way intersection in an area where 3- and 4-way intersections are prevalent). Finding and selecting routes in one environment that resemble routes in another distant environment (e.g., finding the most similar route) can yield multiple and interesting benefits. In this work we adopt the framework for cycling routes and introduce and address four relevant application scenarios.

2 APPLICATION SCENARIOS FOR CYCLISTS

The route selection framework [4] can serve multiple purposes. Four application scenarios become eminent:

(1) **Ecological validity.** When designing experiments for the evaluation of a novel bike navigation system, one of the most important experimental decisions concerns the proper selection of test routes. The selected routes should represent the relevant environment in order to allow to generalize the findings as much as possible.
(2) **Replication.** Replication of research in different geographic regions is crucial for multiple reasons, e.g., for validation purposes, but also for measuring effects other than the ones resulting from the environmental conditions, e.g., cultural effects.
(3) **Comparison.** Being able to run experiments on similar routes might allow to compare different navigation systems. This can be achieved even though the experiments have been performed at different geographic areas, without having to replicate the experiment of the other system entirely in order to get the results for comparison.
(4) **Recreation.** Apart from the introduced scientific and experimental purposes, this adapted framework can also be utilized for recreational, entertainment and sports purposes. For instance, a cyclist can select a route for her training fulfilling personal criteria, find comparable routes to challenge a peer cyclist from an other city or country, or even prepare for a race competition by training in her local surroundings.

3 ROUTE SELECTION FOR EXPERIMENTAL AND RECREATIONAL PURPOSES

To address the application scenarios introduced in section 2 we consider Vienna, Austria as our baseline. Data from Florence, Italy and Bremen, Germany will be used in order to exemplify the scenarios in different geographic areas. The route features have to be defined, then the data have to be acquired and processed, and finally, the routes have to be selected by the framework [4].

3.1 Route Features

While designing a navigation experiment or preparing for a bike tour, the route selection is crucial. Each route is characterized by a large number of features, and a subset of them can be selected to extract a relevant route. In order to address the application scenarios and exemplify our approach, the following feature categories were selected:

(1) ***Number of decision points***, i.e., intersections. Start and end points are not considered as decision points. This is a hard criterion which is set before the actual analysis starts. Hence, it has no associated weight.
(2) ***Cardinality of decision points***, i.e., the average number of options a decision point has and the number of n-way intersections on the route, see Table 1.
(3) ***Frequency of turn types***, i.e., the number of left and right turns, as well as the number of non-turns.

(4) ***Regularity of decision points***, i.e., the sum of angles the options at a decision point need to be rotated in order to create a regular intersection [2]. This way the type of street network (e.g., gridded) can be approximated.
(5) ***Bearing of the route***, i.e., the orientation of street segments with respect to true north.
(6) ***Length-related features***, i.e., the total route length as well as the mean, standard deviation and median for the segment lengths of the route.

The above features were considered in order to find an average route in Vienna. The number of decision points was set to 12 (excluding start and end point) in order to avoid trivial route length, in terms of decision points. The route length was limited to be between 2 and 3 *km*, which provides rides of around 10 minutes [3]. The features were considered equally important for our experiment and were therefore equally weighted (for more details see [4]). It is important to stress that these feature categories and weights can be extended (e.g., by slope or route safety) or changed according to needs and data availability.

3.2 Data Acquisition and Preparation

The directed bike networks were downloaded via the OSMnx python package [1]. This data was the basis for four of the feature categories, except for *Number of decision points* which was set a-priori to 12 and the *Regularity of decision points* which was calculated according to [2]. In order to compute all possible routes with a given number of decision points Sagemath 9.1 with its SubgraphSearch function[1] was used. All routes containing at least one 2-way node were excluded.

3.3 Baseline - Average Route in Vienna

The bike network of Vienna (*"Wien, innere Stadt"*) consists of 938 nodes and 2 091 edges. There are 2 617 610 possible routes of 12 decision points in this area, from which 18 146 have a length between 2 and 3 km. According to Mazurkiewicz et al. [4] the average route (ranked highest according to weighted euclidean distance based on z-scores), will be considered as representative route. First, the *best possible route* is computed, which is likely a non-existent and hypothetical route. The following steps are necessary: (1) all absolute values for each route are transformed into positive z-scores (whether these values are over- or undershooting the mean is irrelevant); (2) the *best possible route* is created, which is a hypothetical route containing the lowest z-score for each subcategory. In a perfect world this hypothetical route would have a z-score of 0 for each subcategory.

Having the *best possible route*, the *weighted euclidean distance* between this route and any possible route is calculated. All feature categories are equally weighted with 0.2 (the category *Number of decision points* is not weighted since it is a hard criterion). This value gets split equally over all subcategories of a category, example: The category *Frequency of turn types* has a weight of 0.2. Therefore, all three subcategories, number of right, left and non-turns get a weight equal to $\frac{0.2}{3} = 0.06$. The route with the smallest weighted euclidean distance is the most average one (see Figure 1a). It has to be noted, that the results of this framework should be considered as suggestions, serving as a recommendation that requires human inspection, since we might not have all the relevant data in order to avoid unusual cases (see Section 4).

Having computed the average route in the city of Vienna, the four application scenarios can be addressed. For all four cases, the most similar route in Bremen and Florence have to be computed. The only thing that has to be adapted in our framework is *the best possible route*. We will do the same computations for the other two cities as we did for Vienna, but this time, the average route computed for Vienna will serve as *the best possible route* instead of the hypothetical route with the minimum z-score for each subcategory.

[1] http://sage-doc.sis.uta.fi/reference/graphs/sage/graphs/generic_graph_pyx.html#sage.graphs.generic_graph_pyx.SubgraphSearch, last access 04.02, 2021

(a) (b) (c)

Fig. 1. Routes generated by the framework (in red). White dots indicate intersections in the bike network (in blue). Base layer : OpenStreetMap. (a) The average route in Vienna, scale 1:10 000 (b) The most similar route in Florence, scale 1:13 000 (c) The most similar route in Bremen, scale 1:10 000.

Table 1. Characteristics of the average route in Vienna and the most similar routes in Florence and Bremen. Abbreviations used: Seg. - segment, M. - mean, St. dev. - standard deviation, Med. - median, W. - weighted

City	Avg. Options	# Intersec.			Regularity			# Turns			Length-related Features				W. M. Bearing
		3	4	5	3	4	5	r	l	s	Total Length	M. Seg. Length	St. dev. Seg. Length	Med. Seg. Length	
Vienna	3.67	5	6	1	55.77	15.69	83.17	4	4	4	2259.58	173.81	169.98	88.51	174.86
Florence	3.58	7	3	2	60.11	109.39	78.10	2	4	6	2203.30	169.48	185.06	92.17	174.13
Bremen	3.42	7	5	0	68.18	37.30	NA	2	4	6	2178.39	167.59	211.47	74.93	195.33

3.4 Most Similar Routes for the Application Scenarios

The corresponding bike networks for Florence (*"Firenze, centro storico"*) and Bremen (*"Bremen, Altstadt"*) consist of 1 960 and 442 nodes and 3 901 and 1 018 edges, respectively. In Florence there are 70 726 routes of 12 decision points and a length between 2 and 3 km, whereas Bremen has 55 548 of those. The street networks differ concerning the intersection types, e.g., in Florence there are 7-way intersections which are not present in Vienna (see Section 4). If subcategories in either Florence or Bremen were not identical with those ones in Vienna we excluded routes where one of those subcategories was not 0, e.g., all routes with at least one 7-way intersection from Florence were excluded (the subcategories for 6-way intersections are missing in Table 1 because the most average route in Vienna had zero 6-way intersections and the most similar routes in Florence and Bremen too). Again, the absolute values were transformed into z-scores for each city respectively. Now, the *best possible route* is the average route in Vienna, which was calculated previously. The absolute values of this route were converted into z-scores based on all other routes in Florence and Bremen, respectively. Next, the *weighted euclidean distance* was calculated for each route. The route with the smallest distance is the most similar one to the average route in Vienna, given these subcategories and weights (see Figures 1b and 1c). Several similarities can be recognized. All routes have a part which goes back and forth. Furthermore, all routes have one segment oriented towards south/south-west which comes after the back and forth part of the route.

4 DISCUSSION AND CONCLUSION

The presented application scenarios in Section 2 were addressed in the following way. The selected route in Vienna, can serve as a representative route for performing a cycling experiment that can generalize to a certain degree, thus addressing the fist application scenario. The computed routes in Bremen and Florence are the most similar to the one selected in Vienna, thus allowing to replicate the experiment, addressing the second application scenario. Similarly, the same routes could be used for the evaluation of a novel navigation system, allowing to compare the results against the results obtained by evaluating the navigation system in Vienna, addressing the third application scenario. Finally, in the same manner, setting the *best route* to fulfill certain criteria might allow to optimize training sessions as well as be used to satisfy recreational purposes, e.g., by weighting land cover parameters higher in order to compute a scenic route.

In this work we demonstrate (1) a systematic approach for choosing a route for a cycling experiment and (2) how to find similar routes in other geographical areas. The framework should be utilized as a recommendation system requiring human rating before choosing a route in order to avoid selecting unrealistic routes due to data limitations. Therefore, it is important to validate several suggestions given by our framework in order to choose an appropriate one. On the other hand, if the resulting routes are generally unusual, the categories and/or weights should be adapted accordingly.

Another aspect which should be discussed is how to handle differences in city properties. We excluded those routes which had other properties that the average route in Vienna. There are several ways to handle this case. One possible way of handling this issue, assuming that the missing property (in the average route) is important for the user, is adding the mean value from the population of all routes to the target route. Another possibility would be to adjust the weights, under the assumption that 7-way intersections are more similar to 6-way intersections than 3-way intersections considering special aspects and therefore preferred. In our work, we presented only routes with the smallest weighted euclidean distance. It is still uncertain how big a difference must be in order to yield different study results. Therefore, it would be interesting to use the route as an independent variable in future experiments in order to see if indeed different results originate from choosing different routes in terms of weighted euclidean distance. The presented framework is flexible and new categories can be added. Furthermore, the weights allow to favor routes with specific characteristics. Our approach depends greatly on data availability and processing. In order to lower the entry barrier an API[2] will be provided which will help to select and compare routes from different geographic areas for pre-computed attributes.

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[2]See https://geoinfo.geo.tuwien.ac.at/index.php/resources/ for updates

CHAPTER 4

Replication of Wayfinding Studies in Different Geographic Areas. A Simulation Study

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Author's Contribution: conceptualization, methodology, software, formal analysis, investigation, data curation, writing — original draft preparation, writing — review and editing, visualization

Replication of Wayfinding Studies in Different Geographic Areas. A Simulation Study

BARTOSZ MAZURKIEWICZ AND IOANNIS GIANNOPOULOS

Research Division Geoinformation • TU Wien • Gusshausstraße 27-29• 1040 Vienna, Austria

E-Mail{bartosz.mazurkiewicz, ioannis.giannopoulos}@tuwien.ac.at

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Summary: *Replication of real-world wayfinding studies is not a trivial task. Even less if it is to be replicated in a different geographic environment. The selection of one or several routes is one of many decisions to be made. Only recently (2021), a reproducible, systematic and score-based approach for route selection for wayfinding experiments was published. Besides allowing for selecting a route within a selected experimental area, it claims to be able to find similar routes in different geographic areas. However, it remains unclear if similar, according to this route selection framework, routes lead to similar study results. In order to answer this question, an agent-based simulation comparing Turn-by-Turn and Free Choice Navigation approaches (between-subject design) is run in one European (Vienna) and one African (Djibouti City) city. First, a route in Vienna is selected and, second, the 5 most and the 5 least similar routes in Djibouti City are found. These routes are used in the simulation in order to scrutinize if more similar routes lead to more similar results regarding the arrival rate as a metric. The results suggest that the route selection framework is suitable for replication studies for the Turn-By-Turn navigation approach but needs further improvement for the Free Choice Navigation approach by adding features describing the neighborhood of the route.*

1. Introduction

The replication of studies is not a trivial task, as many factors need to be considered and kept as similar as possible to make the results comparable. The route selection is crucial for replicating wayfinding studies. There are two possibilities regarding the experimental area. It can be kept constant, although some elements of the environment may have changed over time and potentially impact study results. The second option is to replicate a wayfinding study in another geographic area. In the second case, the route selection task is not as simple as in the first case (using the same route). The routes from both studies, the original and the replicating one should be similar regarding the wayfinding task.

We recently presented (2021) a framework [14] that allows systematic route selection, i.e., how to select a route from a given experimental area with many potential routes. Furthermore, we hypothesized that this framework would increase the replicability of wayfinding studies by finding similar routes in different geographic areas. If this assumption can be verified, then the above-mentioned problem of selecting similar routes in different geographical areas can be solved or at least mitigated. Therefore, we will use the previously proposed route selection framework, first, to identify an average-based [14] route in a European city (Vienna) and, second, to find the most and the least similar routes in Djibouti City in Africa. Two navigation systems (see Section 3.2) will be compared on these routes with respect to the arrival rate. Since the framework can capture route characteristics, more similar routes in Djibouti City should lead to more similar results to those achieved in Vienna. As in our previous study [13], this hypothesis will be scrutinized through a simulation study.

The contribution of this work is two-fold: First, the suitability of the route selection framework for replication studies is investigated. Our results suggest the ability of the route selection framework to support replication studies in other geographic regions. Furthermore, it should increase the comparability of wayfinding studies if the selected experimental areas with their respective routes are similar enough. Second, we shed light on the importance of route selection in wayfinding studies by analyzing the arrival rates on single routes.

2. Related Work

In this section, we discuss relevant literature, first, about reproducibility in the domain of GIScience in general and, second, about replication in the wayfinding domain. In this work, the terms reproducibility and replication are used in the sense of Claerbout/Donoho/Peng [2]. Reproduction means recreating the results with the same methods and input data that the authors provide. The related concept of replication means coming to the same conclusion by conducting a new study.

2.1 Reproducibility in GIScience

Reproducibility has seen considerable interest in the GIScience domain within the last years (e.g., [9, 3]). Ostermann and colleagues assessed 87 papers from GIScience conferences between 2012 and 2018 regarding reproducibility [17]. None of the assessed works was easily reproducible. This study replicated a study considering the AGILE conference [16]. In conclusion, both conference series are similar regarding reproducibility. Konkol and colleagues conducted a study about computational reproducibility in geographic research [10]. They studied the understanding of open reproducible research (ORR) through surveys, interviews and a focus group. They found that the meaning of ORR diverges considerably among the participants of the European Geosciences Union General Assembly 2016. Furthermore, the authors tried to reproduce the results and figures of 41 open access articles from Copernicus and the Journal of Statistical Software. They encountered technical issues of different severity levels in 39 works.

2.2 Replication in Different Geographic Areas in the Wayfinding Domain

Several studies have been conducted replicating real-world studies in virtual environments. Kuliga and colleagues [11] conducted a wayfinding study in a building and then replicated it three times in different virtual replicas. All four conditions yielded similar results regarding superfluous distances and absolute angular pointing errors. Savino and colleagues compared wayfinding in real-world and virtual environments [20]. They found differences between both navigation aids (paper map and smartphone) in both conditions regarding stopping time and task load, among others. No new route was selected in both studies, as the virtual environment reflected the real world.

Wayfinding studies replicated or conducted in a different geographic area are usually based on questionnaires rather than actual wayfinding studies (see e.g., [12, 15]). To the best of our knowledge, there is no work replicating an actual pedestrian wayfinding task in a different geographic area. One reason for this might be the difficulty of selecting appropriate routes. Our work contributes to the realization of replication studies in the wayfinding domain, which are conducted in different geographic areas by facilitating the route choice.

In many wayfinding experiments (e.g., [6, 5]) in which at least two navigation systems are compared, one of the conditions is a map-based Turn-By-Turn navigation approach (e.g., Google Maps). The replication of this widespread baseline condition is rather simple (App availability) but still time-consuming. Given that many empirical results are available for this and other approaches, there might be a possibility to avoid the replication of baseline approaches in every experiment. This would allow comparing novel systems against existing ones by reproducing the experimental setup but having to collect the results for the novel approach only.

3. Experimental Setup

In this section, the agent-based simulation study with its two navigation systems, Turn-by-Turn (TBT) and Free Choice Navigation (FCN), is described in detail. We will elaborate on both experimental areas and all potential routes with pre-defined features. As in our previous work [13], the study follows a between-subject design with 6000 agents. The choice between a between-subject or within-subject design is of less importance, as long as both groups do not differ significantly regarding their environmental spatial abilities (see Section 4), which mainly influence the performance (see Section 3.2).

3.1 Experimental Areas

As the original experimental area (source city), the city center (surface area 2.5 km^2) of Vienna is chosen (see Figure 1). According to the classification by Thompson et al. [22], the network layout is of type high transit. The city for which suitable routes for a replication study need to be found is Djibouti City in Africa (see Figure 2), which is of network type irregular [22]. The selected experiment area is of similar size (surface area 2.27 km^2) and lies in the western Part of Djibouti City (see Figure 2). The size of the experimental areas is of less importance, as long as there are routes of the desired length (see Section 3.3). Bigger experimental areas mean more potential routes and result in longer computation times.

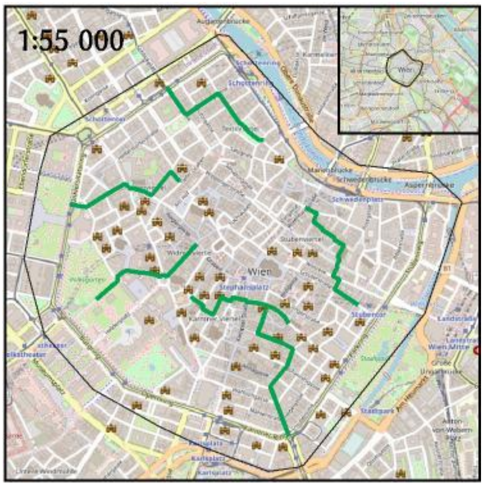

Figure 1: The experimental area in Vienna with six sample routes. Basemap © OpenStreetMap.

Figure 2: The experimental area in Djibouti City with six sample routes. Basemap © OpenStreetMap.

For both experimental areas, the raw network data were downloaded from OpenStreetMap (OSM)[1]. The intersections and their characteristics were calculated using the Intersections Framework [4], whereas street segments between two intersections were extracted with a custom script. For both areas, a networkx graph was created, which was used for the simulation.

3.2 Navigation Systems

Following our previous work [13], we compare the same two navigation approaches, namely

[1] https://www.openstreetmap.org, last access March 25th, 2022

Free Choice Navigation (FCN) and Turn-by-Turn (TBT). The primary reason to use a navigation assistance system is the desire to reach a defined destination. Therefore, the arrival rate is chosen as the success metric. An agent successfully reaches its destination if the walked distance does not exceed 150% of the shortest path length [13].

3.2.1 Turn-by-Turn (TBT)

In this condition, the agent will be guided along the shortest path between origin and destination and receives only at turning points navigation instructions. It is a popular approach that is often used as baseline in navigation experiments (e.g., [8, 21]). Whenever agents have to go straight ahead (continuation within a 20° cone concerning the current walking direction) at a junction, then no instruction is issued, and the agent will not turn. Every agent has a fixed probability to interpret generic navigation instructions correctly, which ranges between 0.8 and 1. We expect such a high probability [13] because navigation instructions are followed every day by millions of users. The agent interprets a turning instruction using a weighted random choice: The branch indicated in the instruction obtains a weight equal to the agent's probability to interpret generic navigation instructions correctly. The remaining probability is distributed equally over all remaining branches, excluding the one indicated in the instruction and the most recently taken branch. Once the agent reaches the destination, the trial ends.

3.2.2 Free Choice Navigation (FCN)

Free Choice Navigation is a navigation paradigm aiming for more freedom of choice during navigation, trying to balance the number of free choices, given instructions and a maximum allowed route length [13]. The following example shows the working mechanism: Anna, a good wayfinder, navigates to an art gallery. Before the navigation starts, Anna receives information about the beeline direction and distance to the art gallery. The system does not issue any instructions at the first two junctions because the beeline direction should still be clear to the user after such a short period. In this situation, Anna decides on her own which branch to take. The third junction, however, is rather complex and has six branches. Anna is quite sure about the beeline direction towards the art gallery, but two branches seem to be good choices to her. Based on internal computations which take her spatial abilities and the environmental structure into account, the navigation system becomes aware of this difficulty (see our previous work [13]). Consequently, Anna receives an instruction because one of the branches results in a considerable deviation from the acceptable route length. The instruction is interpreted correctly and Anna continues her way to the art gallery.

This example illustrates which components influence the internal computations of the navigation system: the user's environmental spatial abilities, the features of the current junction and the already traversed route. If an instruction is issued, a similar procedure as above applies, with the difference that the last taken branch is not excluded but has a lower probability of being taken. Another difference is that the agent's probability to interpret the generic navigation instruction correctly (as well between 0.8 and 1) depends linearly on its environmental spatial abilities. For more details, please refer to the original paper [13].

3.3 Route Selection

In this section, an average-based route in the source city and the most/least similar routes in the target city are selected. Our previously proposed route selection framework was used for these tasks [14].

As pre-emptive criteria [14], we set the route length between 550 m and 1000 m (see e.g., [18, 19]) and the number of decision points on a route to 12 (according to OSM) to avoid trivial route length. Only shortest paths were considered suitable for our experimental design. Given that the two navigation approaches depend on the geometry of the route and the network (see Section 3.2), geometry-based routes features were selected [14]: average number of branches, number of n-way intersections (e.g., 3-way intersections), regularity of decision points [4], number of right, left and non-turns and length-related features (average, median and standard deviation of segment lengths and total route length). All features were equally weighted. To find all possible routes meeting the set criteria, we followed the original paper

[14] and used SageMath 9.1 with its SubgraphSearch function[2]. In Vienna, 11737 shortest paths meeting the above-mentioned criteria were found and 9064 in the experimental area in Djibouti City.

3.3.1 Vienna

For every route in Vienna, the weighted Euclidean distance (called score) to the hypothetical route, which shows closest to average values for all criteria, was calculated [14]. Four routes yielded a minimal score of 0.12 (0 would indicate a perfect match). Actually, there are only two distinct routes, since every route is present twice. Two distinct routes traversed from start to destination and vice versa result in four routes. All four routes are very similar, and they differ regarding the direction and a turn while entering a square (see Figure 3). Due to these similarities, no route could be defined as better than the others, and consequently, all four routes are considered suitable.

For each of these routes, the five most and five least similar routes in Djibouti City were found using the framework. Five routes were chosen due to two reasons. First, arrival rates for five routes are more representative than considering one route only. Second, five seems a reasonable number in the route selection process because higher-ranked routes may not always be suitable for the experiment due to uncaptured characteristics in the route features (e.g., data not available). In this case, lower-ranked routes need to be considered too. The route selection framework is an assistance system, and local knowledge will always help to make the final decision, potentially excluding higher-ranked routes. This expert knowledge does not impede reproducibility, if the decision is well documented.

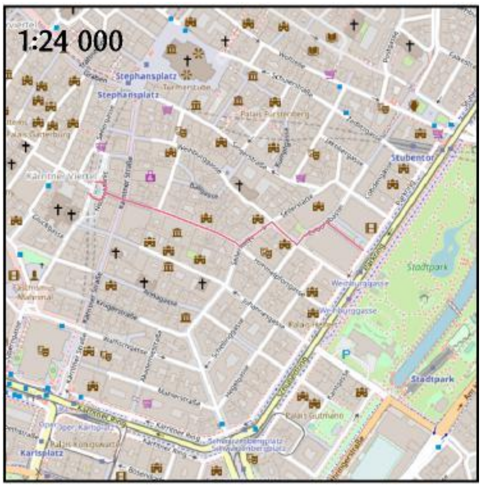

Figure 3: Routes in Vienna. The four routes differ in direction and a turn while entering a square. Basemap © OpenStreetMap.

3.3.2 Djibouti City

While searching for the most and least similar routes in Djibouti City, two further features were added to increase the similarity to the source routes. Both features concentrate on the order of one of the above-mentioned features (see Section 3.3). The sequence of right, left and non-turns (e.g., 'rnrlrnl') and the sequence of the cardinality of decision points (e.g., '3334343') along the route were considered, as they potentially influence the simulation results (e.g., more branches lead to more difficult decisions).

In Vienna, the Euclidean distance was calculated between every route and a hypothetical average route (hence the term average-based). In Djibouti City, the latter is substituted by the routes found in Vienna, respectively (see Section 3.3.1). As the two newly added features are strings, the Levenshtein distance was used to calculate the difference.

[2] https://doc.sagemath.org/html/en/reference/graphs/sage/graphs/generic_graph_pyx.html, last access March 4th, 2022

For each of the four considered routes coming from the source city, the five most and least similar routes in the experimental area in Djibouti City were calculated. The Euclidean distances for the most (M=0.903, SD=0.096, MIN=0.683, MAX=1.022) and least (M=3.334, SD=0.417, MIN=2.49, MAX=3.641) similar routes differ considerably.

4. Simulation Results

For each route, the whole simulation was run 100 times in order to counterbalance the influence of the weighted random choice function (see Section 3.2). Each route was walked by two (TBT and FCN) groups of 3000 agents. The presented numbers are the means of the corresponding route(s) for all 100 runs (different seeds). To ensure that the common ability of agents to interpret navigation instructions correctly did not influence the results, a Wilcoxon Signed-Rank Test on these abilities of the agents was performed. No significant (α = .05) differences between both conditions were found n = 3000 (Z = .00, p = .99, r = .00). The general influence of the these abilities on the Free Choice Navigation approach was discussed in our previous paper [13]. For each city, the parametrization (FCN) with the best balance between arrival rate and freedom of choice was used [13].

Vienna			Djibouti City			
			Most Similar Routes		Least Similar Routes	
Route	TBT	FCN	Mean TBT	Mean FCN	Mean TBT	Mean FCN
0	0.962	0.954	0.923	0.857	0.854	0.916
1	0.966	0.96	0.953	0.905	0.846	0.909
2	0.967	0.932	0.962	0.906	0.856	0.914
3	0.951	0.953	0.956	0.909	0.854	0.916

Table 1: Arrival rates for four equivalent (Euclidean distance score) routes in Vienna and their five most/least similar counterparts in Djibouti City. TBT - Turn-By-Turn, FCN - Free Choice Navigation, Mean - mean for 5 routes. The figures are rounded to three decimals.

4.1 Vienna

In the European city, both navigation systems reached a high arrival rate of around 0.95 (see Table 1). On three routes (0-2), TBT led more agents to the respective destination than FCN. On one route (3), FCN performed better than TBT. In general, the achieved arrival rates in Vienna are very similar for both navigation systems.

4.2 Djibouti City - Turn-By-Turn

For agents using the TBT navigation system, the most similar routes in Djibouti showed an arrival rate of around .95, which is close to the arrival rate in Vienna (see Table 1). The first route (0), however, is an exception, having a lower arrival rate of .923. The least similar routes in Djibouti showed an arrival rate of around .85, representing a considerable difference to both the most similar routes and the routes from the source city. For every route from the source city, the most similar routes in the target city yielded more similar results than the least similar routes.

4.3 Djibouti City - Free Choice Navigation

For agents using the FCN navigation system, the most similar routes in Djibouti showed an arrival rate of around .9, which is different from the arrival rate in Vienna (around 0.95, see Table 1). The first route (0), again, is an exception having a lower arrival rate of .857. The least similar routes showed an arrival rate of around 0.91, similar to the most similar routes. Moreover, the least similar routes in Djibouti yielded higher arrival rates than the most similar routes.

4.4 Djibouti City - TBT versus FCN

Comparing both navigation systems on the five most similar routes in Djibouti City shows that more agents reached their destination with TBT than with FCN. The opposite is observed while considering the least similar routes. In this case, FCN is superior to TBT regarding the arrival rate (see Table 1).

5. Discussion and Limitations

This section will discuss the results by comparing the arrival rates between and within cities, navigation approaches and the most and least similar routes. Furthermore, we discuss the limitations of our work.

The four selected routes in Vienna yielded similar arrival rates for both navigation systems (see Table 1). Only one route (2) led to a bigger difference of around 3%. This is not in line with the original work [13] in which TBT had, on average, a 5% higher arrival rate (100% vs. 95%). This indicates that route selection is crucial in experimental design because it can change the drawn conclusions and the outcome of a wayfinding study. For the TBT condition in Djibouti City, the route selection framework helped to find routes that yield, on average, a similar arrival rate as the corresponding source route. The least similar routes yielded considerably worse results (around 85%) compared to both the source routes in Vienna and the most similar routes in Djibouti City. This indicates the suitability of the route selection framework with the selected route features, as the lower-ranked routes yielded less similar results than higher-ranked routes. As Vienna and Djibouti City represent quite different layout types [22], we expect the framework to work as well in other geographic areas.

The FCN condition in Djibouti City shows a different picture, in which both the most similar and the least similar routes yielded high arrival rates but not as high as the source routes (see Table 1). Moreover, the least similar routes yielded better results in terms of arrival rate than the most similar routes. This can be explained by the interplay between the chosen route features and the navigation approach. One of the ideas of Free Choice Navigation is to give more freedom to the wayfinder. This increases the chances of not taking the shortest path, which is supposed to be taken in the TBT approach. The simulation data support this hypothesis (see Table 2).

Vienna			Djibouti City			
			Most Similar Routes		Least Similar Routes	
Route	TBT	FCN	Mean TBT	Mean FCN	Mean TBT	Mean FCN
0	107	597	79	344	52	282
1	105	601	85	658	58	242
2	121	380	89	375	57	190
3	139	398	67	329	52	282

Table 2: Number of uniquely walked routes taken by successful agents for four equivalent (regarding the Euclidean distance score) routes in Vienna and their five most/least similar counterparts in Djibouti City. TBT - Turn-By-Turn, FCN - Free Choice Navigation, Mean - mean for 5 routes. The figures are rounded to integers.

In the FCN condition, more unique routes are taken by successful agents in both Vienna and Djibouti City. With an increasing number of unique routes, the neighborhood around the route plays a more vital role. A route might be easy to navigate, but once a navigation error occurs, the wayfinder might find itself in a difficult to navigate area due to complex junctions, dead-ends or detours [1]. The selected properties (see Section 3.3), however, regard route properties only, without considering the neighborhood of the route itself. The route selection framework could be improved by including additional features, which capture the previously used characteristics but adapted for the neighborhood. Completely new features like centrality measures (graph theory) calculated for the route neighborhood could also help to improve the process of finding similar routes. This could be as well a first step to tackle the problem of conducting the baseline condition over and over again in wayfinding experiments (see Section 2.2). Previously collected empirical data could be used as a proxy if the neighborhoods and routes are highly similar.

However, the definition of such a neighborhood is not a trivial task and depends on the navigation system. Some routes are more likely to be taken with a given navigation system. We suggest incorporating features describing this neighborhood while considering the navigation system to define its spatial extent. One possibility to define the spatial extent of the route's neighborhood is the Potential Route Area (PRA) [8]. However, the PRA is based on shortest paths only, which are not necessarily taken.

The selected metric is important too. Regarding the number of unique routes (see Table 2), the results are as expected, more similar routes yielded more similar results than less similar routes. Regarding the arrival rate, the results are partially in line with our expectations (see Table 1). Therefore, the selected route features should consider the navigation system and the success metric.

The achieved arrival rates in Djibouti City are not entirely in line with the previously conducted simulation study [13]. Our study used 40 (Djibouti City) routes instead of the whole route population as in the original paper. A wayfinding study is usually conducted with a small-sized subsample of routes. The differences within the cities (see Table 1) and between our study and the original work [13] suggest that the selected route can impact study results (see Section 6).

5.1 Limitations

We could have added more complexity to the simulation with respect to the original study, but we wanted to keep our results comparable. In order to find similar routes, other similarity metrics could have been used. Toohey and Duckham [23] compare four different trajectory similarity measures, but all of them rely purely on route geometry. Han and colleagues used deep learning to calculate route similarity [7]. The authors, however, define the similarity based on node-wise distance over the underlying spatial network, although their architecture incorporates information about direct neighbors for a node, whose importance can be set by a parameter. In contrast to the selected route selection framework [14], however, the resulting similarity is not readily explainable.

6. Conclusion and Future Work

In our work, we wanted to verify if the proposed route selection framework can find similar routes in different geographic areas and, thus, make it suitable for replication studies. Our results reveal the suitability for the widespread Turn-By-Turn navigation approach and suggest the incorporation of further neighborhood features into the framework in order to work with navigation approaches that cover more potential routes between start and destination like Free Choice Navigation. This work is a first step towards the replication of wayfinding studies in different geographic areas.

For future work, there are several strands to follow. Further success metrics needs to be tested with our approach to see whether the results are applicable beyond the arrival rate and the number of uniquely walked routes. The definition of the neighborhood for a route is an open problem. We believe that it should depend on the tested navigation system. Furthermore, features describing this neighborhood are to be defined and verified. Our results suggested the importance of route selection on study results. We will scrutinize this hypothesis with a further simulation study in which we will run a wayfinding experiment on all suitable potential routes within the experimental area and compare the results. A further research direction is the prediction of the arrival rate or any relevant success metric based on the route and neighborhood features without running the simulation. One possibility would be the usage of deep learning.

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CHAPTER 5

Rethinking Route Choices! On the Importance of Route Selection in Wayfinding Experiments

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Rethinking Route Choices! On the Importance of Route Selection in Wayfinding Experiments

Bartosz Mazurkiewicz
Geoinformation, TU Wien, Austria

Markus Kattenbeck
Geoinformation, TU Wien, Austria

Ioannis Giannopoulos
Geoinformation, TU Wien, Austria

Abstract

Route selection for a wayfinding experiment is not a trivial task and is often made in an undocumented way. Only recently (2021), a systematic, reproducible and score-based approach for route selection for wayfinding experiments was published. However, it is still unclear how robust study results are across all potential routes in a particular experimental area. An important share of routes might lead to different conclusions than most routes. This share would distort and/or invert the study outcome. If so, the question of selecting routes that are unlikely to distort the results of our wayfinding experiments remains unanswered. In order to answer these questions, an agent-based simulation study with four different sample sizes (N = 15, 25, 50, 3000 agents) comparing Turn-by-Turn and Free Choice Navigation approaches (between-subject design) regarding their arrival rates on more than 11000 routes in the city center of Vienna, Austria, was run. The results of our study indicate that with decreasing sample size, there is an increase in the share of routes which lead to contradictory results regarding the arrival rate, i.e., the results become less robust. Therefore, based on simulation results, we present an approach for selecting suitable routes even for small-scale in-situ studies.

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1 Introduction

Novel navigation system paradigms for wayfinders are still the subject of ongoing research. Regardless of the target group, i.e., whether it would be pedestrians [5, 7, 12], cyclists [20, 16] or car drivers [11] many decisions during experimental design must be made. While these decisions may impact the study results, this impact is often neither evident nor easy to estimate. One of these decisions relates to the selection of a route suitable for a particular wayfinding study. Given a potential experimental area of non-trivial size, there are at least thousands of potential routes researchers can select from (see Section 3). The potential influence of different routes on study results, however, has not been scrutinized systematically. Given the myriad of potential routes and the different characteristics they come with, there might be an important share of routes that lead to study results deviating from the mean calculated over all possible routes (population mean). By means of an agent-based simulation study comparing two different navigation approaches for all potential routes in a selected experimental area, we will provide evidence that with decreasing sample size, the share of routes which lead to contradicting results increases. Given these differences in results, we

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propose a selection process of appropriate routes, i.e., routes that provide stable results across sample sizes and lead to results congruent with the population mean. Hence, our approach is useful for route selection in comparative wayfinding studies, even for smaller sample sizes.

We will provide evidence that route selection is a crucial step in experimental design, as it shows the potential to turn around the study results. Therefore, more attention should be given to this phase of experimental design. Our approach can be combined (see Section 5.3) with route selection methods for wayfinding experiments (see e.g., [15]), which have been proposed so far.

2 Related Work

In this section, two branches of related work will be discussed. First, we review systematic approaches for route selection during experimental design and route justification. Second, we will discuss comparative wayfinding studies which involve at least two routes and examine whether the route itself was treated as an independent variable in the analysis.

2.1 Systematic Route Selection for Wayfinding Studies

In our previous work, we did an exhaustive search of 'six major venues (conferences and journals) in the broader area of geographic information science and related fields' [15, p. 2] between 2010 and early 2020 regarding route descriptions and/or justifications in studies involving wayfinding tasks with a predefined route. In total, 32 papers fell into this category. The conclusion was that, in general, route choice was poorly justified and that only half of the selected publications mentioned the route length, which was considered a basic feature. This leaves the impression that route selection in wayfinding experiments tends to lack appropriate justification, given the potential impact a route may have on results. In very recent studies (i.e. from 2020 onwards), examples of both missing and explicit route selection justification can be found. Dong and colleagues [3] compared augmented reality (AR) and 2D navigation electronic maps in pedestrian wayfinding. The selection of three experiment routes was not explicitly justified. There are as well examples of explicit and elaborated route justifications. Benelia compared paper maps with audiovisual Turn-by-Turn (TBT) instructions in the context of spatial learning for car drivers [2]. While selecting the route, Benelia tried to maximize personal safety, to avoid high levels of stress in participants and to have sufficient stimuli along the route. Another example of explicit route justification can be found in [20] comparing TBT and ACTF (As-The-Crow-Flies) navigation approaches for cyclists. Both routes used in this publication were designed to contain a segment on which the participant had to cycle contrary to the compass direction pointing to the destination. This feature was crucial to the experimental design.

Although both examples present an explicit justification for route selection, they are not necessarily reproducible because several routes with those characteristics are possible and they might lead to different results. In order to tackle this problem, we previously proposed a methodological average-based framework for systematic and reproducible route selection [15]. All possible routes are ranked according to criteria and corresponding weights, which the researcher must set. This flexibility allows finding routes that exactly fit the requirements of the study. However, our framework does not provide any information on how the routes may impact the study results.

2.2 Comparative Wayfinding Studies and the Importance of Route as Independent Variable

This section will review comparative wayfinding studies and verify whether the route was used as an independent variable, thereby providing examples for both cases.

It is not new to consider the route itself an important variable in comparative wayfinding studies. Savino and colleagues [20] considered the potential influence of the two selected routes in their comparative wayfinding study for cyclists and, in consequence, analyzed the data for each route separately. For both routes, the authors came to the same conclusion regarding differences in route length, task load and orientation. However, the number and the type of errors committed differed. Dong et al. compared two navigation systems on three different routes [3]. In their ANOVA analysis, the route was treated as a factor. For none of the compared eye-tracking metrics, `route` yielded a significant effect. It was only significant for the metric wayfinding duration, which is expected as route lengths differed and were not normalized. Moreover, without justification, the authors do not include route as a predictor (logistic regression) when analyzing the sketch maps. Richter et al. compared consistent and inconsistent navigation instructions on eight routes in a desktop virtual environment [18]. The selected routes had a similar number of turns and a landmark at every intersection. In the analysis, the potential influence of the route was not considered. Kuo and colleagues compared four different navigation systems on four different roads in a virtual reality (VR) environment [9]. Here, the route was also stated to be used as one of four predictors (linear regression). However, this variable, as well as two further ones, were not mentioned in the analysis. Therefore, it remains unclear if the route had an effect on the results, although this expectation was made explicit. Another study conducted in VR compared three AR-based navigation interfaces on three different routes [21]. The routes were designed to have the same length, number of turning points and street crossings. To each interface, exactly one route was assigned. The route was not treated as a factor, and in the end, it is unclear whether the observed effects come from the navigation system, the route or a combination of both.

Generally speaking, only a few routes are compared within a single wayfinding study, which seems reasonable from a research economics perspective. Simulation studies, however, are a notable exception. Amores and colleagues [1] proposed a novel navigation paradigm *most recoverable path*. Their approach was tested by means of a simulation study in Quito, Paris and Melbourne in which 13500 routes per city were selected. However, they analyzed the influence of network topology on their approach but did not analyze the data on a route level. Another example of a simulation study in which a novel navigation paradigm was proposed is our previously published work [14]. We tested our approach with 100 routes in Vienna, Djibouti City and Mexico City, respectively. Differences between those cities were found, but route-wise differences were not analyzed.

Taken together, these examples give the impression that route selection is not always given sufficient relevance, even though it might have an impact on study results. There is no systematic approach, first, to show that different routes may lead to different results, and second, how to select routes for a wayfinding study congruent with the population mean of all routes. This paper aims to fill these gaps.

3 Experimental Setup

In this section, the agent-based simulation study is described in detail. We will elaborate on the experimental area and all potential routes with pre-defined features, such as route length. Furthermore, the sample sizes and both navigation approaches, namely Turn-by-Turn (TBT) and Free Choice Navigation (FCN), will be described. The study follows a between-subject design comparing two navigation systems.

3.1 Experimental Area and Potential Routes

As the experimental area, the city center (surface area 2.5 km^2) of Vienna, Austria is chosen (see Figure 1). According to the classification by Thompson et al. [22], the network layout is of type *high transit*. For this area, the raw network data were downloaded from OpenStreetMap (OSM)[1]. The intersections and their characteristics were calculated using the Intersections Framework [4], whereas street segments were extracted with a custom script. Taking these pieces together, the city center is represented as a networkx graph having 1848 nodes and 2722 edges.

For every experimental design, several decisions regarding route choice have to be made (e.g., route length, sequence of left, right and non-turns, number of decision points and experimental area). In order to reduce the search space of potential routes, we will consider only shortest path routes (see e.g., [19]) with 12 decision points [15] and a length between 550 m and 1000 m (see e.g., [17, 19]) in order to avoid trivial route length on the one hand and, on the other hand, to ensure a reasonable duration for an in-situ study (1000 m would result in a duration of 12.5 minutes based on an average walking speed of 4.85 km/h [10]). In order to find all possible routes sharing these characteristics and comprising no loops, SageMath 9.1 with its SubgraphSearch function[2] was used, as in our previous work about the route selection framework [15]. The resulting $N_r = 11373$ routes are the whole population of routes being shortest paths and matching the mentioned lengths and number of decision points and were used for the simulation, which was implemented in Python 3.6.

3.2 Sample Size

The simulation is run with four different samples sizes ($n = 15, 25, 50, 3000$ agents) following a between-subject design. The first three sample sizes can be considered realistic in wayfinding studies [21, 18, 20, 9, 6]. The largest sample size ($n = 3000$) is considered to be representative for the whole population of participants of such studies. Different sample sizes are tested in order to investigate whether the sample size impacts the results for both a single route and the whole route population. Each group navigates each of the 11373 routes.

3.3 Navigation Systems

The presented simulation approach will work for any two navigation systems, as we want to demonstrate that the comparison results may vary depending on the route choice. However, we continue our previous simulation study [14] and compare Free Choice Navigation (FCN) and Turn-by-Turn (TBT). While the particular figures will likely change for other navigation approaches, the proposed route selection process (see Section 5.2) based on the results remains unchanged.

[1] `https://www.openstreetmap.org`, last access February 4th, 2022
[2] `https://doc.sagemath.org/html/en/reference/graphs/sage/graphs/generic_graph_pyx.html`, last access January 30th, 2022

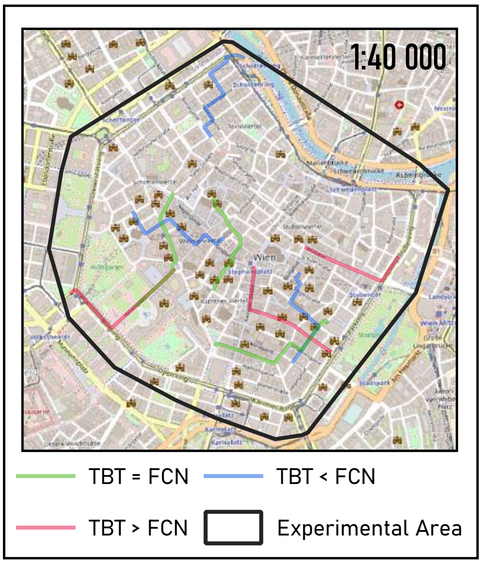

Figure 1 The experimental area in Vienna, Austria and 9 sample routes on which one navigation system performed better or they performed equally well across sample sizes. Basemap OpenStreetMap.

As the primary purpose of navigation systems is to assist wayfinders in reaching the destination, we choose arrival rate as the success metric. However, any other suitable success metric can be chosen by the researcher. As in our previous work [14], an agent is considered successful if it reaches the destination within 150% of the shortest path length. In the same work, we compared these two navigation systems in three different cities [14]. TBT lead between 5% and 10% more agents to their destination in all cities. Now, the main features and mechanics of both navigation approaches will be described.

3.3.1 Turn-by-Turn (TBT)

By analogy with commercial wayfinding assistance systems for pedestrians, the agent is supposed to follow the shortest path between origin and destination and receives navigation instructions at turning points only. If agents have to go straight ahead at a junction, then no instruction is issued and the agent continues straight.Going straight ahead is considered walking in a direction that does not deviate by more than 10 degrees to either side from the current one. Every agent has a probability to interpret a generic navigation instruction correctly. If an instruction is issued, the agent interprets it based on a weighted random choice: The branch to follow, indicated in the instruction and following the shortest path from the current junction, is assigned a weight equal to the agent's probability to interpret generic navigation instructions correctly. The remaining probability is split equally over all remaining branches (excluding the one indicated in the navigation instruction and the one the agent has come from). The trial ends when the agent reaches the destination.

3.3.2 Free Choice Navigation (FCN)

Free Choice Navigation is a novel navigation paradigm aiming for more freedom of choice during navigation [14]. The system allows the agent for some exploration but, on the other hand, tries to avoid costly mistakes by weighing the number of free choices, the number of given instructions and a maximum allowed route length. The working mechanism can be seen in the following example: Alice, a good wayfinder, is navigating to a museum. Before the navigation starts, the system gives her information about the beeline direction and distance to the museum. At the first two junctions, the system does not issue any instructions because it is assumed that the beeline direction is still clear to the user. In consequence, Alice decides on her own which branch to take. The upcoming junction, however, is rather complex as it has five branches. Alice is quite sure about the beeline direction, but there are two branches that seem equally well suited to her. The system detects this difficulty based on internal computations that take the environmental structure and spatial abilities of the user into account and issues an instruction because one of the branches leads to a considerable deviation from the allowed maximum route length. Alice interprets it correctly and continues her walk.

This example shows that the navigation system issues an instruction based on environmental spatial abilities of a user, the characteristics of the current junction and the already walked route. If an instruction is issued, then the same procedure as above applies with the difference that the branch the agent has come from is not excluded but has a lower probability of being taken. Again, the probabilities of available branches to be taken depend on the agent's probability of interpreting generic navigation instructions correctly, which in turn depends linearly on its environmental spatial abilities. Furthermore, FCN has six parameters that steer when an instruction is given. We used the best parameter set for Vienna, which is a trade-off between the percentage of successful trials and the number of given instructions [14].

For every agent, regardless of the condition, the ability to interpret navigation instructions correctly ranges between 0.8 and 1 and is fixed before the experiment. Please refer to our previous work for further modeling details regarding the agents and their decision mechanism [14].

4 Simulation Results

In this section, we, first, present descriptive statistics for each of the systems separately and, second, discuss the differences originating from different routes. Differences between both conditions are calculated using bootstrapping ($B = 10000$ runs) and 95% confidence intervals (CIs) are reported in square brackets. As mentioned above, the arrival rate (each agent walked each route) for both systems is compared (see Section 3.3). In order to ensure that the common ability of agents to interpret navigation instructions correctly (co-domain [.8; 1] [14]) did not influence the results, a Wilcoxon Signed-Rank Test was performed for every sample size. No significant ($\alpha = .05$) differences between both conditions were found ($n = 15$ ($Z = 1.14$, $p = .25$, $r = 0.29$), $n = 25$ ($Z = 1.17$, $p = .24$, $r = 0.23$), $n = 50$ ($Z = .05$, $p = .96$, $r = 0.01$), $n = 3000$ ($Z = .00$, $p = .99$, $r = 0.00$)). Furthermore, this ability defines good and weak wayfinders. We assured that agents from both groups are present in every sample size, which is a realistic scenario for real-world wayfinding studies. The presented figures are computed based on all potential routes, which were walked by all agents of a given sample size. There are 11 373 potential routes in the experimental area. This is an exhaustive sample considering the selected route features (see Section 3.1).

4.1 Turn-by-Turn

In the case of the Turn-by-Turn condition, the simulation for all four sample sizes yields similar results regarding the arrival rate (co-domain [0; 1])(see Table 1). The mean arrival rate is around 0.97 across all four sample sizes. This is in contrast to the minimum arrival

Table 1 Descriptive statistics of the arrival rate [0; 1] for the TBT condition for all four sample sizes tested in the simulation. The figures are rounded to 3 decimals.

Sample Size	Mean	SD	Median	Min	Max
15	.976 [.975; .977]	.048 [.047; .05]	1 [1;1]	.66 [.66; .66]	1 [1; 1]
25	.975 [.974; .976]	.043 [.042; .044]	1 [1;1]	.68 [.68; .72]	1 [1; 1]
50	.973[.972; .973]	.038 [.037; .039]	.98 [.98; .98]	.72 [.72; .74]	1 [1; 1]
3000	.97 [.97; .97]	.033 [.032; .034]	.982 [.982; .983]	.788 [.788; .798]	1 [1; 1]

rate, which shows considerable variation between sample sizes: For sample size $n = 15$, the minimum arrival rate for a route is 0.66 (only $\frac{2}{3}$ of the agents reached the destination), whereas for sample size $n = 3000$ it is 0.788. The range of the arrival rate decreases with increasing sample size. In order to see whether there are route-wise differences between sample sizes, the range ($max - min$) for every route is calculated (see Figure 2). Over 20% of the routes have a range greater than or equal to 0.05. There is no difference across sample sizes for 716 routes (6.2%), whereas the biggest difference encountered for a single route across sample sizes is 0.25.

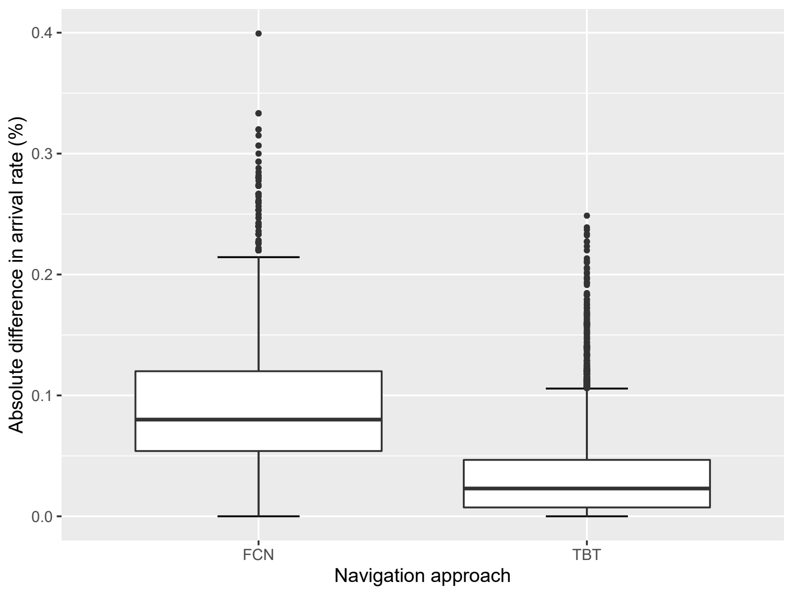

Figure 2 Route-wise ranges ($max - min$) across all sample sizes for the condition FCN (left) and TBT (right).

4.2 Free Choice Navigation

Analyzing all routes together, the four sample sizes yield, again, similar results (see Table 2). The mean arrival rate is approx. 0.90; in contrast to the TBT condition, the range remains almost identical across sample sizes. Route-wise ranges ($max - min$), however, reveal a higher variance in the FCN condition (see Figure 2): More than 80% of the routes show a difference greater than or equal to 0.05 and the biggest difference for a route across sample sizes is 0.4. For 34 routes (0.3%), there is no difference across sample sizes.

Table 2 Descriptive statistics of the arrival rate [0; 1] for the FCN condition for all four sample sizes tested in the simulation. The figures are rounded to 3 decimals.

Sample Size	Mean	SD	Median	Min	Max
15	.919 [.917; .921]	.104 [.099; .109]	.933 [.933; .933]	0 [0; 0]	1 [1; 1]
25	.908 [.906; .91]	.096 [.091; .101]	.92 [.92; .92]	0 [0; 0]	1 [1; 1]
50	.896 [.894; .897]	.091 [.086; .096]	.92 [.92; .92]	0 [0; 0]	1 [1; 1]
3000	.902 [.901; .904]	.08 [.074; .086]	.918 [.917; .919]	0 [0; 0]	.996 [.994; .996]

4.3 Differences within both Systems

In both approaches, of course, the ability to interpret navigation instructions plays a role, but as it is constant for all routes, it is not mentioned as a factor. As indicated by the figures in tables 1 and 2, arrival rates differ between both navigation systems. These differences may stem from navigation system mechanics and street layout. In the TBT condition, routes with less turning points likely lead to a higher arrival rate, as the agent has to make fewer decisions and, in consequence, has lower chances to commit an error. On the other hand, in the FCN approach, route features like junction complexity or junction skewness [4] are likely to play a role. A detailed analysis of route features leading to differences is beyond the scope of this paper (see Section 6).

4.4 Differences between both Systems

Based on the within-system results, both navigation systems will be compared regarding the arrival rate. Again, first, the whole population is analyzed, and second, route-wise differences will be inspected in order to investigate whether sample size impacts the share of routes that lead to contradicting results. Across all sample sizes, the TBT approach leads, on average, more agents to the destination (see Table 3). The sample size with the highest mean difference in arrival rate across routes is $n = 50$, whereas the lowest value can be observed for $n = 15$. Mean, standard deviation, median and maximum values are similar in all simulation runs; however, there are differences in the minimum: All minimum values are negative, meaning that there is at least one route on which the FCN approach performed better than TBT. Therefore, we will inspect per route differences between both conditions by subtracting FCN from TBT arrival rates for the respective sample size.

For every sample size, we count the number of routes which lead to a congruent result with the population mean (TBT performs better), as well as routes on which FCN performed better than or as good as TBT (see Table 4). For the sample size $n = 3000$, which is the most representative one, there are around 8% of routes on which FCN performed better or as good as TBT. For smaller sample sizes, this figure increases, reaching around 47% for $n = 15$. Contrary to the within-system results (see Sections 4.1 and 4.2), here, considerable differences between sample sizes can be observed.

5 Discussion and Limitations

This section will discuss the results, which suggest that route selection is an important part of experimental design and should be given more importance. Furthermore, a methodology that supports informed route selection is proposed. Finally, limitations that apply to our work are addressed.

Table 3 Descriptive statistics for the route-wise difference ($TBT - FCN$) in arrival rate [0; 1] for all four sample sizes tested in the simulation. Positive values mean that the TBT condition performed better and negative values indicate a better performance of the FCN navigation approach. The figures are rounded to 3 decimals.

Sample Size	Mean	SD	Median	Min	Max
15	.057 [.055; .059]	.111 [.107; .116]	.067 [.067; .067]	- .333 [- .333; - .333]	1 [1; 1]
25	.067 [.065; .069]	.101 [.096; .105]	.04 [.04; .04]	- .28 [- .28; - .24]	1 [1; 1]
50	.077 [.075; .079]	.094 [.089; .098]	.06 [.06; .06]	- .24 [- .24; - .18]	1 [1; 1]
3000	.067 [.066; .069]	.081 [.075; .086]	.057 [.056; .058]	- .119 [- .119; - .104]	1 [.983; 1]

Table 4 Shares of routes on which TBT performed better than, as good as and worse than FCN regarding the arrival rate. The figures are rounded to 1 decimal.

Sample Size	TBT Better	TBT = FCN	FCN Better
15	53 %	35.6 %	11.5 %
25	70.4 %	19.3 %	10.3 %
50	84 %	7.5 %	8.5 %
3000	92.1 %	0.1 %	7.8 %

5.1 Discussion

Regardless of the sample size, the simulation, which considers all potential routes in the experimental area, yields similar results, indicating the superiority of TBT over FCN regarding the arrival rate (see Table 3). Looking at the results for the whole population, one might think that route selection is not so critical because, independently of the sample size, the big picture is preserved. This picture is, however, somewhat misleading as wayfinding studies, of course, are conducted with a small-sized subsample of the whole population, considering both routes and participants. By means of keeping the population of routes constant across sample sizes, our simulation results indicate that different routes can lead to contradicting results (see Table 4). In consequence, ad-hoc decisions on route selection can lead to contrary results compared to the whole population of routes. This situation worsens with decreasing sample size as the chance of selecting such a route increases (see Table 4). The results, therefore, suggest that selecting a route is all the more important in the case of small numbers of participants. For samples sizes (n = 15, 25, 50), which can be considered realistic for comparative wayfinding experiments (see e.g. [21, 18, 20, 9, 6]), the probability to select a route that will yield results incongruent with the population mean varies between 16% and 47%. This means, if we planned an experiment with two groups, with 15 participants each, and we randomly picked a route from our experimental area, we would have a 47% chance to conclude that TBT is not superior regarding the arrival rate, although it actually is (see Table 3). Almost every second route would lead to the contrary conclusion in the case of $n = 15$, whereas, for sample sizes $n = 25$ and $n = 50$, it would be every third and sixth route, respectively. Given this high share, we want to draw attention to the importance of the route selection process as it can influence study results, in particular, given the relatively small number of participants, which is quite common in the wayfinding domain.

Taken together, in the selected experimental area, the lower the number of agents, the higher the probability of choosing a route which leads to results that are contradictory to the population mean, i.e., the route becomes more crucial with decreasing sample size. This is a problem as routes often seem to be selected in an ad-hoc manner during experimental design in wayfinding studies (see Section 2.1). Given that wayfinding studies are not conducted with 3000 participants, a method to select those routes which are likely to lead to a conclusion corresponding to the whole population is proposed.

5.2 Route Selection

Depending on the sample size, the chance of selecting a route that leads to conclusions that are not in line with the whole route population may be considerable. This section suggests an approach that allows for an informed route selection. This process is based on the simulation results, i.e., the simulation for the compared navigation systems needs to be run beforehand. It is a two-step approach. First, routes without great variance across all sample sizes are selected, and second, those which lead to results congruent with the population mean (based on the simulation) are chosen. In both steps, the researcher needs to select a filtering threshold depending on the selected performance metric and observed differences. The underlying idea is to select routes that lead to similar results across all sample sizes and are compatible with the population mean. In our example, two navigation systems are compared. Therefore, their differences in arrival rate are used in the presented filtering process. The same approach can be applied with one navigation system only by using the arrival rates directly instead of the differences or any other success metric chosen by the researcher.

5.2.1 Consistent Routes

In this step, routes will be selected which are *consistent* regarding differences in arrival rates, i.e., they do not vary considerably in arrival rates across sample sizes. Given that there are four values (one per sample size) for each route to consider, we refrain from calculating the standard deviation and will consider the range as the measure of variability. The applied measure with a corresponding threshold can be adapted according to the number of tested sample sizes and the researcher's needs. For every route, we calculate the range across all four sample sizes and select those routes whose range is not greater than 0.03, which means that the biggest allowed difference across sample sizes is 3%. This value can be set according to the simulated data. The smaller the value, the more restrictive this filtering step will be. In this case study, 618 (5.4%) routes have a range smaller than or equal to 0.03. By this filtering step, routes with high variance across sample sizes are excluded. However, routes that are not *close* to the population mean are still possible, or even routes on which the drawn conclusion is contrary to the population mean. Therefore, a second filtering step is necessary.

5.2.2 Routes in Concordance with the Population Mean

In order to find routes that are congruent with the most representative sample size ($n = 3000$), they are filtered by their mean across sample sizes. Routes whose means do not differ considerably from the population mean (see Table 3) are selected for being considered suitable routes. For this step, another threshold needs to be selected by the researcher. In consequence, routes are selected whose means do not deviate by more than the selected threshold from the population mean. Given that the population mean difference is 0.067, we set this threshold to 0.02. Therefore, routes with an average between 0.047 and 0.087 are considered in our case study as acceptable. With this second filtering step, 304 routes are left. This is 2.67% of the whole population. For this proof of concept, the exact threshold values are of less relevance. The smaller both thresholds are set, the more restrictive the filtering process is, i.e., less routes are considered suitable. This has to be decided based on the simulation results at hand and the researcher's needs.

5.3 Route Ranking

Our approach delivers a list of suitable routes with regard to the most representative sample size but does not state explicitly which one to choose. Our approach can, however, be combined with our route selection framework [15]. In doing so, potential route biases can be further mitigated. First, the routes are ranked according to features selected by the researcher [15], e.g., mean segment length, traffic, average number of branches or number of left, right and non-turns along the route. Second, the ranked routes are filtered according to our proposed approach. This results in routes that satisfy both the researcher's needs regarding route characteristics and being close to the global mean across sample sizes.

5.4 Limitations

Running a simulation implies simplifying certain aspects of the real world. In our simulation, the street network and the agent's spatial abilities are used to model the agent's behavior. Compared to our previous work [14], the agents, their reasoning mechanism and the environment could have been adapted regarding complexity (see e.g., [13, 8]). In addition to that, there may be relationships that have not been yet discovered and, therefore, are not considered in the simulation process. Given that randomness plays a role in our simulation, running the simulation once is a limitation. However, several seeds were tested with a subset of routes during a pretest and the results were quite consistent.

6 Conclusion and Future Work

By means of an agent-based simulation study, which was run on all potential routes in a selected experimental area, it was shown that depending on the route selection, the study results can be contradictory. Although the results for the whole population lead, on average, to the same conclusion, there is an important share of routes that lead to contrary results. Given that the route selection process usually does not receive much attention in wayfinding studies, with this simulation, we direct researchers' attention to the potentially harmful effects of ad-hoc route selections. Therefore, we propose a selection method based on running the same simulation with different sample sizes. The resulting selection of routes should lead to results that are congruent with the population mean.

Furthermore, our proposed simulation approach with different sample sizes allows for detecting weak points of a given navigation system. Researchers will find routes on which their proposed navigation system does not perform as good as expected and their examinations will lead to further improvements. Moreover, our simulation approach makes it possible to identify spatial configurations (routes and their neighborhood) favorable or adverse to the navigation system at hand by analyzing route features that cause differences in the selected performance metric. This analysis would provide valuable feedback in order to improve the tested navigation approach. The in-depth analysis of route properties and their influence on the success metric is part of our future work. One could improve the navigation system until it is robust on all routes, i.e., it performs equally well on the whole population of routes.

A series of simulation studies in different geographic areas is planned in order to see whether different network types [22] lead to the same results. *Motor cities* might be less vulnerable to ad-hoc route selection. In addition, the route properties which caused differences in arrival rates will be examined in depth. Moreover, we plan as well to increase the complexity of the models to increase the validity of the simulation. Adding more complexity would expand the search space for possible explanations because the differences in the selected success metric could be explained by additionally modeled features like points of interest, buildings or terrain slope.

We are aware that implementing a simulation is not a trivial task and not every researcher has the resources to do it. Therefore, another research direction could be the prediction of route suitability based on route features and the characteristics of the navigation approach without running a simulation study.

Our approach still needs to be verified in real-world environments. Therefore, a series of human subject experiments will be conducted. In these experiments, the results of several routes selected with our approach will be compared with the population mean resulting from a simulation study. Following our selection approach, we expect that those routes considered suitable will lead to consistent and congruent with the population mean results and the routes considered non-suitable will more likely lead to contrary conclusions. However, this hypothesis needs to be verified in a real-world setting as the routes are selected based on simulation results.

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Part 2 – The Potential of Free Choices for Spatial Knowledge Acquisition

CHAPTER 6

Navigating Your Way! Increasing the Freedom of Choice During Wayfinding

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Navigating Your Way! Increasing the Freedom of Choice During Wayfinding

Bartosz Mazurkiewicz
Geoinformation, TU Wien, Austria

Markus Kattenbeck
Geoinformation, TU Wien, Austria

Ioannis Giannopoulos
Geoinformation, TU Wien, Austria

Abstract

Using navigation assistance systems has become widespread and scholars have tried to mitigate potentially adverse effects on spatial cognition these systems may have due to the division of attention they require. In order to nudge the user to engage more with the environment, we propose a novel navigation paradigm called *Free Choice Navigation* balancing the number of free choices, route length and number of instructions given. We test the viability of this approach by means of an agent-based simulation for three different cities. Environmental spatial abilities and spatial confidence are the two most important modeled features of our agents. Our results are very promising: Agents could decide freely at more than 50% of all junctions. More than 90% of the agents reached their destination within an average distance of about 125% shortest path length.

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1 Introduction

Adaptive route instructions for pedestrian wayfinders have seen considerable research interest [7]. At the same time, empirical evidence has been collected which suggests an adverse impact of wayfinding assistance systems on spatial cognition and knowledge acquisition (see e.g., [6]). Routing paradigms which allow wayfinders to make an increased number of decisions and, therefore, reduce the number of instructions given as much as reasonable would be one option to remedy this effect. We explore one possible solution to this problem and propose a pedestrian navigation paradigm which balances the number of given instructions and the freedom of choice left to the user at junctions. We explore the feasibility of this paradigm by means of an agent-based simulation. At the start, an agent is provided with a destination vector, similar to someone pointing to the destination when asked for instructions. Once an agent started walking they do not need to stick to a predefined route, hence they will not suffer from *on-route uncertainty* [22] but are free to make their own decisions at junctions. However, a route instruction will be provided if odds are increased that an agent, based on its current state, is likely to choose a not reasonably good branch at a given junction. The presented paradigm aims for less instructions and more free choices along the route – regardless the way instructions are phrased or the modality they are given in.

Based on a comparison of our routing paradigm (labelled *free choice navigation – FCN*) to the turn-by-turn (TBT) technique, which is prevalent in commercial wayfinding assistance systems, our contribution is threefold:

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1. We present a new navigation paradigm (*free choice navigation*);
2. We provide evidence that agents reach their destinations within a reasonable departure from the length of the shortest path using our approach and
3. We quantify the number of instructions we save/add compared to the baseline (TBT).

Successfully testing of our approach has a potentially important implication: Reducing the number of instructions would provide users of wayfinding systems with more time to observe the environment while, simultaneously, forcing them to engage more with it as they have to make their own decisions. Based on prior evidence (see e.g., [33]), this is expected to result in increased spatial knowledge acquisition (see section 7 below). It is important to note, though, that our approach is meant to be used in a leisure scenario, i.e. in situation in which wayfinders do not feel any time pressure.

2 Related Work

Given our research goal, we discuss three different branches of related work. First, literature on reducing the number of TBT navigation instructions or adapting their structure/presentation is reviewed. Second, we discuss literature using the beeline/as-the-crow-flies navigation approach. Lastly, we review agent-based simulations modeling pedestrian behavior. Taken together, this review reveals important factors which need to be considered when modeling agents and its accompanying mechanics (see also Section 4).

2.1 Enhancing TBT Instructions

In recent years, evidence has been collected which suggests that the use of navigation systems may have an adverse impact on spatial cognition and orientation (see e.g., [6, 21]). This effect is commonly explained by the need to divide the attention between the navigation system and the environment when following a pre-determined route (see e.g., [13]). Possible remedies regarding TBT navigation systems are enhancing instructions with additional information (see e.g., [16, 36]), reducing the number of instructions [28], combining them with different interaction techniques (see e.g., pointing [25]) or providing haptic or audio feedback (see e.g., [12, 14]). All these approaches assume a predefined route. This is in contrast to our paradigm according to which users can make their own spatial decisions to a large extent.

2.2 Beeline Navigation

There are alternatives to TBT navigation approaches, e.g., using the beeline to the destination. One particularly important idea is the so-called least-angle strategy, which was for the first time thoroughly studied by Hochmair and Frank [20] using a simulation study. According to this strategy a user chooses the option with the least angle with respect to the (believed) destination vector. The least-angle strategy has been studied with respect to various implementations: [29] and [8] report on prototype navigation systems for pedestrians which use vibro-tactile feedback devices to indicate the beeline. Either system guides users successfully to their destination. Both systems allow for free exploration but none of them control for an upper path length limit. This is in contrast to our approach: We try to find a compromise between free exploration and maximum path length while determining the point in time at which an instruction needs to be given. Savino and colleagues [30] compare TBT and two different implementations of the beeline approach for cyclists, one of which provides visual cues when the beeline differs from the shortest path branch. The latter approach enhances user confidence. The beeline approach was preferred for leisure scenario. This is in line with prior evidence suggesting that it is important for pedestrians to optimize both, distance and angle [31] and that the environmental complexity [15] has also a major impact on route choice behavior. Our approach takes these findings into account (see Section 4) by providing the beeline at the starting point and providing further wayfinding assistance as needed.

2.3 Simulation Studies and Models of Pedestrian Behavior

As mentioned above, the beeline approach was studied by Hochmair and Frank [20] using a simulation study regarding perception errors. Based on this work, Hochmair [19] analyzed the effectiveness of the least-angle strategy with a simulation study for different transportation modes. The results suggest a limited usability of this approach in real life (human perception and memory errors). Our simulation takes these findings into account by modeling human errors and actively supporting the user if help is needed, moreover, it incorporates environmental spatial abilities and spatial confidence (see Section 4). Other agent-based wayfinding studies frequently focus on collision avoidance (see e.g., [35]), on evacuation (see e.g., [37]) or on the interplay between navigational instructions, the environment and the agent (see e.g., [34, 22]), including research on route choice behavior based on different levels of cognitive maps [10]. Generally speaking, the findings of these papers are based on the assumption that a path a user should follow exists. Again, this is in contrast to our approach. Neither do agents receive an instruction at every decision point, nor is there a predefined path. Our agents are also not equipped with prior knowledge of the environment nor do they know the true destination direction at every junction (which is in contrast to, e.g., the models used by Kneidl [23]), i.e., they are considered to be unfamiliar and, hence, have no cognitive map.

3 Simulation Preparation and Baseline Condition

In order to test[1] our hypotheses (see Section 5) we run an agent-based simulation (non multi-agent) with two conditions. The main focus lies on whether agents do reach their destination with our approach. Consequently, we will not model effects on spatial cognition, e.g. spatial knowledge acquisition as this aspect will be scrutinized in a real-world study (see Section 7). The simulation study was run in three cities with three different network types [32], namely Djibouti City (Djibouti, type: *irregular*), Vienna (Austria, type: *high transit*) and Mexico City (Mexico, type: *checkerboard*). For each city 100 random routes with a length ranging between 500m and 5000m were chosen in order to test the approach on shorter and longer routes. We tested two conditions (*TBT* vs. *free choice navigation*): Each condition was tested with 3000 agents, i.e., there are 6000 different agents (between subject design). The agents are constructed based on the the so-called BDI-framework [27] for practical reasoning: The agents simulate pedestrians who have **B**eliefs about where their destination is located; agents **D**esire to reach their destination; and, finally, they act based on **I**ntentions, i.e., at each intersection they reason about which decision they need to take in order to reach their goal based on their beliefs.

3.1 Software and Data

Several agent-based modeling and simulation frameworks exist [1]. For our approach we utilized python 3.8.8 using the package networkx (v2.5.) [17], avoiding frameworks providing graphical interfaces since this was not relevant for the presented study. The raw network

[1] The terms *junction* and *intersection* are used interchangeably, as well as *option* and *branch* are.

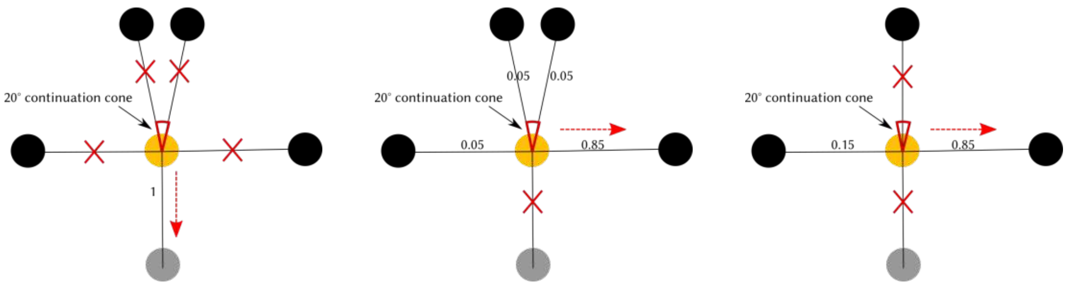
data were downloaded from OpenStreetMap (OSM). The intersections were calculated with the Intersections Framework [11], whereas street segments were extracted with a custom script. With those components each city could be represented as a networkx graph.

3.2 Following Navigation Instructions

In this subsection the modeling aspect which is shared across both simulation conditions, is explained: In either condition an agent has the ability to follow navigation instructions. This ability (*nav_instr*) is modeled using a value in the range $[0.8; 1.0]$ and represents the probability of taking the branch indicated in the route instruction. This ability is expected to be high because navigation instructions are followed on a daily basis by millions of users, hence the interval between $[0.8, 1.0]$. We use a uniform distribution in case of the baseline, whereas a normal distribution is assumed in case of our *free choice navigation* approach (see Section 4).

3.3 Baseline

The baseline our approach is compared with is a TBT navigation system, i.e., agents receive navigation instructions only at turning points. Agents in this condition have a single attribute called *nav_instr* which represents their ability to follow a route instruction correctly. It is represented as a value within $[0.8; 1.0]$ drawn from a uniform distribution, because no figures were found on how well people can follow turn-by-turn navigation instructions in general (i.e., a mean value based on empirical grounds is not available).



(a) **(b)** **(c)**

Figure 1 The decision mechanism for the baseline condition. current node: yellow (in the center); previous node: grey; given instruction: red arrow; excluded branches: red cross; annotations represent the probability of a branch to be taken: (a) turn-around instruction (always performed correctly); (b) Sample turn instr. 1 with two straight ahead options; (c) Sample turn instr. 2 with only one straight ahead option.

There are three options for an agent at any junction: **(1) no instruction** means continue straight ahead (within a 20° cone); **(2) turn-around instruction** which are always followed correctly (see Fig. 1a); **(3) turn instruction** which is interpreted as a weighted random choice (see Fig. 1b and 1c). The decision which segment is taken is modeled as a multi-step process, which starts only if a turn instruction is given: First, all potential options to follow are identified. This means, the option the agent is coming from is excluded because it would have been otherwise a turn-around instruction. If there is only one straight ahead option, it is also excluded too (see Fig. 1c) because no instruction would have been given if continuing straight would have been the correct option. Next, probabilities are assigned to each option: The agent's ability to follow navigation instructions (*nav_instr*) is assigned as a probability to the option which is indicated as correct by the turn-instruction. All other n remaining options have a probability of $\frac{1-nav\_instr}{n}$. Finally, given these probabilities a weighted random choice is performed and the agent moves to the next junction and the procedure is repeated until the agent reaches its destination.

4 Free Choice Navigation Approach

In this section, a detailed account of the *free choice navigation* approach will be given. We, first, describe the properties of our agents and then, we move on to explain the decision mechanism of our agents in detail. In order to mitigate potentially adverse effects on spatial cognition by the usage of wayfinding assistance systems (see, e.g., [21]) we propose the *free choice navigation* approach. This paradigm nudges users to engage with the environment by balancing the number of free route choices against a given maximum distance threshold.

4.1 Agent Properties

Due to the nature of our approach, modeling the agents is more complex than in the baseline condition. Agents have five different properties, each of which is detailed below:

Belief Vector (*belief_vec*) represents a subjective vector from the current junction to the believed location of the destination which, in turn, depends on the agent's current orientation. In contrast, the true destination vector (*true_dest_vec*) is the beeline from the current junction to the true destination location. These two vectors usually differ (see [20] for this claim and Figure 3 for an example).

Environmental Spatial Abilities (*env_sp_ab*) follow a normal distribution ($M = 0.5$, $SD = 0.2$; co-domain $[0; 1]$). They have an impact on the belief vector. They are needed to "form a coherent mental representation" of the environment [39]. To the best of our knowledge, there is no evidence about the distribution of Environmental Spatial Abilities, therefore we assumed a normal distribution.

Spatial Confidence (*conf*) refers to an agent's confidence [39] about the destination direction ($[0.0; 1.0]$). Prior evidence indicates (see, e.g., [26]) that self-reported tests on spatial abilities have been a good performance predictor. We, therefore, model an agent's spatial confidence based on it's environmental spatial abilities: It seems to be plausible to assume that agents which are good wayfinders would indeed have a high self-confidence in knowing the destination direction. Therefore, the maximum (*max_conf*) and minimum (*min_conf*) confidence level of an agent are related to *env_sp_ab* and are set to $env\_sp\_ab \pm 0.2$ (co-domain $[0; 1]$).

Ability to Follow Navigation Instructions (*nav_instr*) represents the ability to follow a navigation instruction (see [34]; see also baseline agents). For this condition it is equal to $env\_sp\_ab * 0.2 + 0.8$; in order to have the same range as for the baseline condition.

Memorized Dead Ends Agents are able to remember dead ends they have already taken in order to avoid back and forth movement (see [19]).

4.2 Initializing Agents

Before an agent starts a trial, both, its environmental spatial abilities (*env_sp_ab*) and its initial spatial confidence (*conf*) value are randomly set according to the intervals described above. Additionally, information about the destination direction is obtained, i.e., *belief_vec* and *true_dest_vec* are pointing to the same direction. In each city the same population of agents is used. A trial is considered successful if and only if an agent has reached the destination deviating no more than a predefined threshold from the shortest path length.

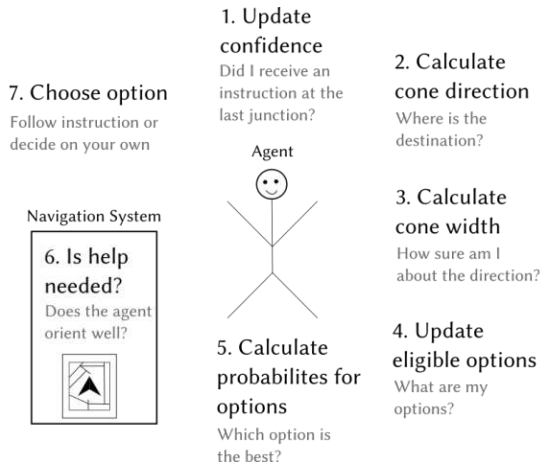


Figure 2 Overview of the decision mechanism for the *free choice navigation* condition.

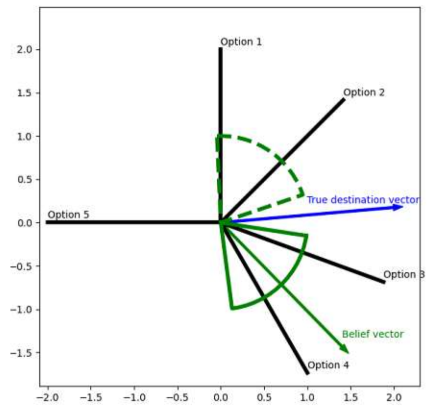


Figure 3 The agent will consider options 3/4 (branches intersect green solid line polygon). The dashed polygon represents the alternative cone (see step 2).

4.3 Decision Mechanism

The key geometric object we use to implement the reasoning of an agent at each intersection is a *cone*. This polygon represents where the agent believes the destination lies in (see Figure 3). The width of the cone (*cone_width*) represents how certain an agent is about *belief_vec*. It is, hence, influenced by *nav_instr*, *conf* and environmental complexity (*env_comp*, see below) and ranges between 360°(total confusion) and 1°(very sure).

Figure 2 provides an overview of the reasoning steps an agent and the simulated navigation system (only step 6) execute. It is important to note that this process will start if and only if the current node is not the goal node nor the current traversed path length is equal or greater than the maximum allowed path length. In both cases the trial would end immediately.

Having said this, the reasoning process starts with the update of the spatial confidence (step 1), based on whether an instruction was issued at the previous junction. Step 2 focuses on the update of its assumption about where the destination is located at. In Step 3 the certainty about this belief vector is modeled. Steps 4 deals with determining the eligible options, whereas a probability is assigned to each of these branches in step 5. Step 6 represents the most important part of this reasoning process, as is now determined whether an instruction should be issued. In a final step, a branch is chosen by the agent (step 7).

The detailed behavior can be described as follows:

Step 1: Update Spatial Confidence

The spatial confidence (*conf*) updates at every intersection[2]. The amount in change is calculated according to equation 1 (as mentioned above, its co-domain is restricted to $[env\_sp\_ab \pm 0.2]$). If an agent received an instruction at the last intersection, the spatial confidence decreases, otherwise it increases. The rationale behind this mechanism is that wayfinders may perceive the fact that they received a route instruction as sign that they have taken wrong decisions in the past. This is, of course, intertwined with spatial abilities and, hence, agents with higher spatial abilities are less prone to loosing their spatial confidence.

$$conf\_corr\_term = 0.05 * (1 - env\_sp\_ab) + 0.01 \tag{1}$$

[2] The spatial confidence will not be updated for the first and the second intersection as no instruction is given at these junctions, see step 6.

Step 2: Calculate Cone Direction

The cone bisector is calculated according to the belief vector (*belief_vec*, see eq. 2). In line with prior evidence [18], the agent's orientation deteriorates with distance (the number of traversed junctions) but less so for agents with higher *env_sp_ab*. For each intersection, this belief vector is rotated away from the *true_dest_vec* by random choice. The rationale for this randomness is that there is no apriori knowledge about in which direction the erroneous *belief_vec* is rotated (see Figure 3).

$$belief\_vec = true\_dest\_vec \pm (1 - \frac{1}{\#traversed\_junctions}) * (1 - env\_sp\_ab) * 180° \quad (2)$$

Step 3: Calculate Cone Width

The width of the cone (*cone_width*) represents how confident an agent is regarding the direction to the destination. It is influenced (see eq. 3) by the agent's spatial confidence and the environmental complexity of the current junction (*env_comp*) whose impact is moderated by the agent's spatial abilities (the lower the environmental spatial abilities the higher the impact environmental complexity shows on the cone width). Before the whole simulation starts each junction in a city will be assigned a normally distributed environmental complexity (env_comp, $M = 0.5$, $SD = 0.2$) which will remain unchanged during all trials. A node for which $env\_comp = 0.5$ is, therefore, considered as decision point having an average environmental complexity. Based on the *cone_width* and the *belief_vec* the actual cone geometry is calculated (see Figure 3).

$$cone\_width = 360° - (conf * 360°) + (env\_comp - 0.5) * 360° * (1 - env\_sp\_ab) \quad (3)$$

Update Eligible Options (Step 4) and Calculate Probabilities for Eligible Options (Step 5)

In order to find the set of eligible branches, agents exclude any already visited dead end (memorized options) from the decision process (Step 4). Having done so, the cone is checked for eligible options and angles with respect to the *belief_vec* are calculated for each branch (Step 5). Three different cases are distinguished:

Option 1: No branch in cone All eligible options are taken into account and the angles between them and the *belief_vec* are calculated (least-angle strategy [20]).
Option 2: Exactly one branch in cone This branch is assigned a probability of 1.0.
Option 3: More than one branch in cone As in this case an agent can choose from several branches inside the cone, angles are found for these by analogy with option 1.

For options 1 and 3, these angles, denoted as *opt_ang*, need to be converted to probabilities using three further steps.

1. All angles are inverted with respect to the maximum angle within the cone which is given by $\frac{cone\_width}{2}$, thereby favoring angles which are closer to *belief_vec*: $inv\_angles = \frac{cone\_width}{2} - opt\_ang$. Subsequently, each inverted angle will be normalized (division by the sum of all inverted angles in the list) in order to ensure that the sum of all probabilities equals one.
2. In order to avoid back and forth movement along the same branch (see [19]), a factor called *already visited penalty factor* (*vis_pen*) is applied to the probability of any edge which has already been visited. The lower the value the higher the penalty. Again, the probabilities are normalized.

3. A final selection step for branches is needed as several branches may show almost the same angle to the bisector of the cone geometry, i.e., whose angles can hardly be distinguished by humans. Therefore, only those branches with a probability greater than $max\_probability - 0.1$ are selected and then the remaining probabilities are normalized.

The above procedure leads to the final set of branches FS with their final probabilities assigned. These will subsequently be used to decide if an agent needs an instruction or not.

Step 6: Determine Whether an Instruction is Given

Given the probabilities and several additional parameters a decision is made whether an instruction is given to the agent[3]. An instruction is provided for any of the following reasons, i.e., the list of reasons is checked one-by-one in the order given below:

1. The shortest path from the current junction to the destination leads over a single segment, i.e., the instruction is given in order to support destination recognition (see [9]).
2. Let *sp_length* denote the shortest path from the start to the destination; let further *dist_walked* denote the distance an agent has walked from the start to the current junction. Finally, let *max_dist* denote the constant factor which determines the allowed deviation from sp_length still rendering a trial successful. Then, the *current buffer* (*curr_buffer*), i.e., the distance an agent can walk from the current junction to the destination in order to still successfully finish a trial is given by equation 4.

$$curr\_buffer = max\_dist * sp\_length - dist\_walked \tag{4}$$

Let, furthermore, *buff_fact* (co-domain: $[0;1]$) denote a factor which is used to balance the number of given instructions against the number of agents that will arrive (given the presupposition that the probability of a successful trial increases for agents who receive more instructions). This means, this factor is used to account for the risk that the agent will exceed the available buffer: An instruction will be given if the current buffer multiplied by the buffer factor is lower than the length of the shortest path from the current junction (see eq. 5).

$$curr\_buffer * buff\_fact < sp\_length\_curr\_jct \tag{5}$$

3. For the same reason other branches are examined (step 2 is introduced in order to save computation time). We evaluate this case based on two steps. We, first, create the set of acceptable branches AB which includes all branches which fulfill inequality 7 in which *sp_over_i* denotes the sum of the length of the shortest path between the upcoming intersection i and the destination and the length of the edge from the current junction to i (see eq. 6).

$$sp\_over\_i = sp\_length_i + len(edge\_to\_i) \tag{6}$$

$$sp\_over\_i <= curr\_buffer * buff\_fact \tag{7}$$

Subsequently, we sum the probabilities of all branches $b \in AB$. If this sum is smaller than a predefined threshold called *pos_sum*, which is kept constant across trials, then an instruction is given.

[3] There is no instruction given at the first two nodes the agent traverses as it is reasonable to assume that the direction of the destination is still evident.

4. An instruction is, furthermore, given if an edge exists in the *final selection* FS (see step 5 above) for which the shortest path from the end node of this edge leads over the current node. Let the current junction be denoted as j_{i-1}; let the upcoming junction of a branch b_i which is part of the final selection set be denoted as j_i. An instruction will be given if the shortest path from j_i would lead over j_{i-1} because this will save agents a loss of *curr_buffer* due to avoidable detours.
5. Given the fact that the number of agents with a successful trial must be maximized, an instruction is also provided if agents have a high probability of choosing a branch which will be costly in terms of the consumed buffer while there would have been "cheaper" alternatives. Let *rem_len_buf* (Remaining Length Buffer, RLB) denote the difference (see eq. 8) between the *curr_buffer* and the *sp_over_i* (see eq. 6).

$$rem\_len\_buf = curr\_buffer - sp\_over\_i \tag{8}$$

Step 1: For all branches $b \in FS$ the ratio between the RLB of the branch with the highest probability and the RLBs of all other branches is checked. If this ratio is larger than a threshold *buff_diff*, this branch will be included in set BS, because it offers a better RLB. If $|BS| = 0$ no instruction is given.

Step 2: If $|BS| \geq 1$: Let $P(b_k)$ denote the probability assigned to the $k-th$ branch and $MAX(P(b_k))$ denote the highest probability of all branches in FS (note: FS is a superset of BS and the probabilities of branches in both sets are the same). For each branch in BS check whether inequality 9 holds in which *prob_diff* denotes a threshold for the ratio of the highest probability of all branches among FS and a given branch in BS.

$$\frac{MAX(P(b_k))}{P(b_k)} > prob\_diff \tag{9}$$

If this inequality holds, an instruction will be given, because chances are high that the agent misses a better RLB.

If none of these cases holds for the current junction, then no instruction is given and and the agent chooses an option (step 7) based on the probabilities (step 5) assigned to each branch. With those conditions we try to predict costly mistakes rather than correct them because some mistakes can be expensive and unrecoverable regarding the goal of reaching the destination within a given distance threshold.

Step 7: Choose an Option

At any junction agents either choose an option by following an instruction or by making a decision without having received an instruction. In the latter case, agents choose the branch they will continue on from the final selection set FS based on a weighted random choice. If an instruction was given, however, the same procedure as for the baseline applies (see above), although one important differences applies: The edge on which an agent traveled to the current junction is the only one which is excluded. Please note: Again, turn-around instructions are as well followed error-free.
This decision mechanism of giving an instruction remains the same for the whole route.

5 Results

In order to reduce the amount of combinations, a pre-test was done with 20 agents (out of 3000) and 15 routes (out of 100) using the following parameter values:

Maximum path length (*max_dist*)	$\{1.2, 1.35, 1.5\}$
Buffer factor (*buff_fact*)	$\{0.5, 0.6, 0.7, 0.8, 1.0\}$
Positive sum threshold (*pos_sum*)	$\{0.5, 0.75\}$
Buffer difference threshold (*buff_diff*)	$\{1.05, 1.2, 1.5\}$
Probability difference threshold (*prob_diff*)	$\{1.05, 1.2, 1.5\}$
Already visited penalty factor (*vis_pen*)	$\{0.1, 0.5, 0.75\}$

This yielded 810 different parameter combinations which were tried. Of those, for each city two parameter sets were chosen for the experiment, resulting in 6 different sets in total:

best_perc is the parameter set which yielded the maximum percentage of successful trials, thereby prioritizing the percentage of agents who arrive.

best_f_ch is the parameter set which represents a trade off (found by multiplication) between the percentage of successful trials and the number of given instructions.

Each of the six parameter sets was used for each city (3000 agents and 100 routes) resulting in 18 runs, overall. Of these, the two best performing runs for each city were selected for the final analysis (see Table 1) applying again the *best_perc* and *best_f_ch* criteria. There are, consequently, two datasets for every city for condition *free choice navigation*. Contrastingly, the baseline has only one dataset for each city as no additional parameters except *nav_instr* need to be set. An overview of the results is presented in Table 2. Generally speaking, more people arrive with the baseline condition across all cities. The parameter set for *best_f_ch* leads to a similar number of instructions per traversed node as for the baseline.

Table 1 The best parameter set for every city regarding *best_perc* (%) and *best_f_ch* (% * f_c). D – Djibouti, M – Mexico, V – Vienna.

City	Best at	max dist	buff fact	pos sum	buff diff	prob diff	vis pen
D	%	1.5	0.5	0.75	1.2	1.2	0.5
M, V	%	1.5	0.5	0.75	1.5	1.5	0.1
D, M, V	% * f_c	1.5	0.7	0.75	1.5	1.05	0.5

Next, we will present the analysis regarding our hypotheses. In order to analyse differences between both conditions bootstrapping ($B = 10000$ runs) was used and 95% percentile-based confidence intervals (CIs) are reported in square brackets. We refrain from calculating statistical tests due to the very large sample size. While there is a single dataset in the baseline condition, for our *free choice navigation* approach the relevant dataset (*best_perc* or *best_f_ch*) is chosen as appropriate.

In the following, we detail several hypotheses with respect to our approach and provide the results of our analysis.

Reduced Number of Navigation Instructions (H1) As described above (see Section 1), *free choice navigation* approach equips wayfinders with flexibility in terms of route choice. We, therefore, hypothesize that people who reach the destination within a distance of $1.5 \times sp\_len$ using our approach will receive less route instructions as compared to the baseline scenario.

Table 2 Comparison of baseline (B) and *free choice navigation* (FCN) for agents who arrived within a certain percentage (leftmost column) of the shortest path length being allowed to walk 150% of the shortest path. Parameter sets for condition *free choice navigation* are given in Table 1 (*max_dist*=1.5). *base*: dataset of baseline; *best_perc*/*best_f_ch*: datasets of *free choice navigation*; %: percentage of people who arrived; ipn: mean no. of instructions per traversed junction (ipn).

City	Djibouti						Mexico						Vienna					
Con.	B		FCN				B		FCN				B		FCN			
Dset	base		*best_perc*		*best_f_ch*		base		*best_perc*		*best_f_ch*		base		*best_perc*		*best_f_ch*	
Feat.	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn	%	ipn
110%	0.74	0.37	0.13	0.66	0.04	0.27	0.81	0.32	0.13	0.62	0.06	0.30	0.77	0.39	0.12	0.61	0.03	0.20
120%	0.9	0.39	0.30	0.68	0.11	0.28	0.95	0.33	0.32	0.66	0.16	0.31	0.92	0.4	0.34	0.64	0.12	0.24
130%	0.96	0.39	0.51	0.7	0.24	0.31	0.98	0.33	0.55	0.69	0.30	0.33	0.97	0.40	0.59	0.67	0.25	0.28
140%	0.98	0.4	0.76	0.72	0.45	0.36	0.99	0.33	0.78	0.72	0.52	0.37	0.99	0.41	0.83	0.69	0.48	0.34
150%	0.99	0.4	0.91	0.74	0.81	0.43	1.0	0.33	0.9	0.74	0.81	0.43	1.0	0.41	0.95	0.71	0.85	0.41

Our figures do not support this hypothesis: For all cases, the mean difference in instructions given per traversed junction[4] between the baseline and our approach (*best_f_ch*) is negative, i.e., less instructions were given in the baseline condition: For Djibouti ($M = -0.037$, $SD = 0.0004$,[-0.0379; -0.0361]) our approach yielded on average one additional instruction every 27 ($\frac{1}{mean}$) junctions, whereas in Mexico ($M = -0.103$, $SD = 0.0004$, [-0.104; -0.102]) this value increases to every 10 junctions. The smallest difference between the two conditions was found for Vienna ($M = -0.004$, $SD = 0.0004$, [-0.005; -0.003]) where one additional instruction every 250 junctions is expected.

Longer Routes Enable More Free Choices (H2) Based on the fact that longer routes result in an increased maximum absolute route length and in line with H1, we also assume that successful agents will have made a higher number of free choices on longer routes. Similar to H1, our results (*best_f_ch*) do not support this hypothesis. We found a weak negative Spearman correlation between the number of junctions traversed and the % of free choices of all decisions an agent made across cities. Djibouti ($M = -0.168$, $SD = 0.002$, [-0.172; -0.164]) and Vienna ($M = -0.179$, $SD = 0.002$, [-0.183; -0.175]) showed a stronger correlation than Mexico ($M = -0.119$, $SD = 0.002$, [-0.123; -0.116]).

Percentage of People Reaching Destination (H3) The *free choice navigation* we suggest imposes increased cognitive load on wayfinders: They have to make spatial decisions based on path integration and their belief about the destination vector (see Section 2). Therefore, we hypothesize that, within a given maximum distance threshold (150%), more people will arrive at the destination with the baseline than with our *free choice navigation* approach.

Our data is in line with this assumption. Again, the difference between the baseline and *free choice navigation* (*best_perc*) is reported: In Djibouti ($M = 0.085$, $SD = 0.0005$, [0.084; 0.086]) on average 8.5 percentage points less trials ended successfully. In Mexico ($M = 0.100$, $SD = 0.0005$, [0.099; 0.102]) the figures show 10 percentage points. For Vienna ($M = 0.047$, $SD = 0.0004$, [0.046; 0.048]), again, the smallest difference compared to the baseline was found, showing an average difference of 4.7 percentage points.

Low Spatial Abilities of Failures (H4) Based on the need to make their own spatial decisions (see also H2), we assume that the fraction of people, who is not able to arrive at the destination within a threshold of $1.5 \times sp\_length$, will be highest within those agents who show low spatial abilities.

[4] The number of obtained instructions was normalized by the number of traversed nodes as *free choice navigation* agents walked on average more.

Table 3 Numbers regarding failed trials: a) Share of failed trials per city and ability category. b) Share of agents who failed at least once.

(a) The share of failed trials within a 150% distance threshold categorized by city and env. spatial abilities.

City	Low	Medium	High
Djibouti	25.95	6.95	1.34
Mexico	28.99	7.68	0.79
Vienna	16.47	3.46	0.23

(b) Share, mean (M) and standard deviation (SD) of agents for a given category of env. spatial abilities **who failed one or more trials**. *low* (521): $[0; 0.3]$; *medium* (2028): $(0.3; 0.7]$; *high* (451): $[0.7; 1]$

City	Low			Medium			High		
Feat.	%	M	SD	%	M	SD	%	M	SD
D	100%	.2	.079	99%	.50	.11	79%	.79	.07
M	100%	.2	.079	98%	.50	.11	51%	.77	.06
V	100%	.2	.079	86%	.49	.10	20%	.75	.05

In order to investigate this hypothesis, agents are categorized, based on their *env_sp_ab* and its standard deviation, into 3 groups: low ([0;0.3], $N_{low} = 521$), medium ((0.3;0.7], $N_{med} = 2028$) and high ((0.7;1], $N_{high} = 451$). The data obtained by the simulation (*best_perc*) supports our assumption: Across cities (*best_perc*) agents with *low env_sp_ab* show the highest share of failed trials (see Table 3a). Moreover, each agent with low spatial abilities failed at least on one trial (see Table 3b). In Vienna 20% of high-level agents did not reach their destination *at least once*, whereas in Djibouti and Mexico this share was 79% and 51%, respectively.

Higher Spatial Abilities Yield Shorter Routes (H5) Based on prior evidence on path integration (see e.g., [24]) we assume that wayfinders with high spatial abilities will be able to take shorter routes, in terms of deviation from shortest path length.

There is a strong negative correlation between *env_sp_ab* and the path length (*best_perc*); which supports this hypothesis. Both, Djibouti ($M = -0.50$, $SD = 0.002$, [-0.504; -0.498]) and Mexico ($M = -0.507$, $SD = 0.002$, :[-0.51; -0.504]) show similar correlations, whereas Vienna ($M = -0.566$, $SD = 0.001$, [-0.568; -0.563]) shows a stronger correlation.

6 Discussion and Limitations

We will discuss the results of our agent-based simulation along two lines. First, we will discuss our findings and contributions with respect to the idea of *free choice navigation*. Second, we will continue with respect to the plausibility of the model and its limitations.

6.1 Discussion

Using TBT navigation systems, users are required to follow a predefined route including predefined turns. This system behavior, however, results in a reduced interaction between users and the spatial environment, ultimately leading to (potentially) adverse effects in terms of spatial orientation. The primary goal of this paper is, therefore, to propose the concept of *free choice navigation* and initially test this assistance approach by means of a simulation study. Our approach has the potential to remedy these effects and is expected to foster spatial knowledge acquisition as it aims to give user more freedom and, at the same time, ensures reasonable route lengths.

Generally speaking, plausibility and validity are both important concepts in simulation studies [5]. While the former can be be judged according to specific figures, the latter requires empirical evidence. Checking validity must, hence, be left for future work (see Section 7); our figures, however, indicate the plausibility of agent behavior. Our *free choice navigation* approach is plausible as cities with different morphologies [32] yield different results (see Tab. 2) which is also in line with prior evidence (see e.g., [4]). This difference is also reflected in our results regarding H1: Our approach does not yield less navigation instructions per traversed node compared to the baseline system. While the effect can be neglected for Vienna (average route length: 87.8 junctions, i.e., 0-1 instructions more than the baseline system) and is of low relevance for Djibouti (mean length: 67.5 junctions, i.e,. 2-3 instructions more), a considerable increase (mean length: 70.6 junctions, i.e., 7 instructions more) can be seen for Mexico City, where 10% more instructions are needed than in the baseline condition. The reasons as well as the impact on user experience leaves much room for further research.

The plausibility of our model is further supported by our results regarding H3, H4, H5: Less people arrived with our approach than in the baseline condition (H3), agents with low environmental spatial abilities fail more often (H4) and the higher these abilities the shorter the path taken (H5). In addition to that, each agent which has low abilities does not reach its destination at least once (see Table 3b). All of these results are in line with our expectations and, taken together, suggest that environmental spatial abilities play a key role (see future work below). Having said this, the simulation results for our *free choice navigation* approach yield, moreover, promising results with respect to success rate (i.e., reaching the destination within $1.5 \times len(shortest\_path)$) and distance traveled: In each city more than 90% of all agents arrive within this threshold. More importantly, on average this upper limit was not reached at all (Djibouti: $M = 1.26$, $SD = 0.13$; Mexico: $M = 1.25, SD = 0.127$; Vienna: $M = 1.25$, $SD = 0.121$). A mean detour of about 25% seems reasonable in a leisure scenario and our approach yields shorter average distances than reported in other, vibro-tactile based, beeline studies (see e.g., [29] in which mean distances greater than $1.5 \times len(shortest\_path)$ are reported). While the number of route instructions issued is not less than for the baseline system the *free choice navigation* approach proposed allows for a particularly high share of free choices (Djibouti: 0.57, Mexico: 0.57, Vienna: 0.59) which results in a lot of engagement with the spatial environment traversed. Having said this, however, our results do not support hypothesis H2: We found a weak negative correlation between the number of traversed intersections and the share of free choices along a route (i.e., the number of intersections at which no route instruction is given): One possible reason for that can be that the parameter set produces an artifact in the data, hence, further research is needed. Furthermore, the higher overall success rate and the lower share of agents with medium and high environmental spatial abilities which did not arrive at least once (see Table 3b) suggest Vienna to be easier to navigate than Djibouti and Mexico City.

Taken together, this discussion reveals that the *free choice navigation* is reasonable. At the same time, the chosen parameters are crucial for the figures achieved. Clearly, our model is not optimal and can, therefore, act as a baseline other researchers can compete with. There are several possibilities for improvement: For example, reducing the number of instructions or increasing the percentage of arrived agents. As a consequence, the data will be published at `https://geoinfo.geo.tuwien.ac.at/resources/`

6.2 Limitations

Despite the promising results, several limitations apply. On the one hand, the environment can be modeled more complex considering for example junction geometry [11] or environmental data like building footprints or points of interests. On the other hand, a more elaborate modeling of agents is feasible, in particular with respect to interpretation of route instructions (of different types) [34] or by considering further wayfinding preferences [3]. A further limitation of our work is related to the application of the introduced cone (see Section 2) for real scenarios. We assumed to know the approximate direction that agents would follow (i.e., the direction of the cone). To apply this to humans, it is necessary to know the direction they will follow. Recent research in human activity recognition has shown very positive results (e.g., [38, 2]), which can be used for our purpose to determine the direction of the cone.

7 Conclusion and Future Work

We introduced *free choice navigation*, a novel approach with the intention to increase the freedom of choice during navigation. This approach was evaluated by means of an agent-based simulation study and compared against a TBT approach, serving as a baseline. The agent-based model used for the simulations is a further contribution, introducing the concept of the *cone*, which encodes the user's spatial abilities and confidence. Our findings are in line with our expectations concerning the proportion of free choices during navigation as well as the impact of spatial abilities on the effectiveness of our approach. Furthermore, the results confirm the plausibility of the introduced agent-based model.

Future human subject experiments in real-world environments are required in order to address a series of open research questions. First, the validity of the presented agent-based model could be investigated by comparing the simulated results with the ones obtained from humans in a real environment. Furthermore, we expect that the *free choice navigation* will foster spatial knowledge acquisition due to the increased engagement with the environment. Along the same line, also aspects concerning user experience, cognitive load, or uncertainty should be addressed in human subject experiments. The data and model will be made available and can serve as a baseline for further development. The model and the results can, thus, be used by the community as a benchmark for future iterations of the model.

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CHAPTER 7

Free Choice Navigation in the Real World: Giving Back Freedom to Wayfinders

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Free Choice Navigation in the Real World: Giving Back Freedom to Wayfinders

Bartosz Mazurkiewicz *, Markus Kattenbeck and Ioannis Giannopoulos

TU Wien, Research Division Geoinformation, 1040 Vienna, Austria

* Correspondence: bartosz.mazurkiewicz@tuwien.ac.at

Abstract: In recent years, there has been collected evidence suggesting that increased usage of navigation assistance systems has a harmful effect on spatial cognition, including spatial knowledge acquisition. Previously, we proposed a potential remedy called Free Choice Navigation (simulation study). This novel navigation approach aims to provide the user with more freedom while navigating, and simultaneously give fewer navigation instructions. This approach also aims at increasing engagement with the environment and fostering spatial knowledge acquisition. We conducted a human-subject study with 48 participants comparing Free Choice Navigation with the widespread Turn-by-Turn approach on the outskirts of Vienna, Austria. The study showed the viability of our navigation system in real urban environments, providing fewer navigation instructions compared to the Turn-by-Turn approach (relative to the number of traversed junctions). Fewer instructions and forced engagement with the environment, however, did not result in differences concerning spatial knowledge acquisition, but interestingly, Free Choice Navigation users (without a map) could extract spatial configuration information similarly well as Turn-by-Turn users having a map. Moreover, we provide evidence that people are interested in learning more about their environments and are willing to walk longer routes to achieve it.

Keywords: wayfinding; free choice navigation; spatial knowledge acquisition; pedestrian navigation system

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1. Introduction

Navigation is an everyday task performed by billions of people. It is composed of wayfinding (the cognitive aspect of planning the route towards the destination) and locomotion (e.g., body movement while avoiding obstacles) [1]. Sometimes, this task has to be conducted under time pressure (e.g., going to a meeting or catching a bus). On the other hand, there are situations, such as going for a walk or visiting a city as a tourist, in which the user would have time to pay attention to the environment. In both scenarios, a smartphone device is commonly utilized as a wayfinding assistance system to reach the desired destination. There is increasing empirical evidence suggesting an adverse impact of these systems on spatial cognition. Mitigating this potentially adverse impact is the topic of current research (e.g., [2–5]).

In a previous work [6], we proposed a navigation approach called *Free Choice Navigation* (FCN) that, among other things, attempts to mitigate these adverse effects. The core idea of FCN is to provide the user with more freedom while navigating compared to a predefined route, as the user has to make own decisions at several junctions. By this, we expect more engagement with the environment. Free Choice Navigation attempts to balance the number of free choices, given instructions, and the route length. An agent-based simulation study showed promising results regarding the number of free choices and the arrival rate for our navigation approach [6]. At more than 50% of all junctions, agents could freely decide which street segment to take. Depending on the city (Mexico City, Vienna, and Djibouti City), between 90% and 95% of the agents found their destination successfully.

Following up on these promising simulation results, we conducted a real-world study in Vienna, Austria, comparing our navigation approach with the widespread *Turn-by-Turn* (TBT) approach. This study allows for assessing the impact of FCN on spatial knowledge acquisition (SKA), an aspect that was not part of the simulation study. Furthermore, it allows for validating the simulation results obtained previously. The contribution of our work is sixfold (order reflects importance):

1. We provide empirical evidence that participants can reach the destination successfully with our novel system approach (FCN);
2. We show that FCN leads to less navigation instructions (relative to the number of traversed junctions). This gives potentially more time for interaction with the environment;
3. We provide empirical evidence that FCN in its current form does not impact spatial knowledge acquisition in comparison to TBT;
4. We show that FCN users have high configuration knowledge, although no map is provided.
5. We present data demonstrating that people are willing to take longer routes while obtaining more freedom and/or spatial knowledge in return and;
6. We present the first application of the *Route Selection Framework* [7] in a real-world study.

We would like to stress that Free Choice Navigation is intended for use in situations with no time pressure. As our approach is rather complex, we provide high-level information about its mechanics (see Sections 2.2 and 4.3.2). For detailed algorithmic information, we refer to the paper that introduces the technical details [6].

2. Related Work

We will discuss three strands of related work. First, we discuss the widely used TBT approach with its potential negative impacts on spatial cognition. Second, we discuss potential improvements of this approach to remedy these effects. Finally, we discuss other navigation approaches that are not exclusively based on turn instructions, such as beeline navigation or Free Choice Navigation. Where applicable, we report on the influence on spatial knowledge acquisition.

2.1. Turn-by-Turn Navigation and Its Disadvantages

The Turn-By-Turn (TBT) navigation approach is based on instructions given at turning points. It is widely used by pedestrians, cyclists, and car drivers (e.g., Google Maps Navigation), and it comes in many shapes (e.g., [8–11]) such as annotated paper maps, mobile maps indicating the route or augmented reality (AR) cues placed in the environment. Besides auditory instructions played at turning points (e.g., [10]), there have also been further non-visual approaches, trying to navigate users through the environment without the need to refer to a display for instructions. Giannopoulos et al. [12] introduced GazeNav, a gaze-based navigation approach providing vibrotactile feedback whenever the correct street segment was gazed at. Although this navigation approach is efficient in reaching the destination, there is empirical evidence supporting that the usage of navigation assistance systems, mainly based on the TBT approach, may have an adverse effect on various aspects of spatial cognition.

Hejtmánek and colleagues showed that participants who spend more time with a GPS-like map acquire less accurate spatial knowledge in a virtual environment [13]. Furthermore, participants with less time spent on a GPS-like map walked shorter routes without the help of an assistance system. Ishikawa [14] concluded that users with increased usage of navigation systems tend to travel less efficiently without GPS-based assistance, have lower spatial abilities regarding mental rotation, and show inferior knowledge about the structure of the walked routes. Ruginski and colleagues [15] found a detrimental indirect influence of using GPS-based navigation aids on environmental learning by influencing spatial transformation processes such as mental rotation [16] and perspective-taking [17]. Dahmani and Bohbot, like Ishikawa [14], assessed the frequency of use of GPS-based navigation systems [18]. Their results show that users with more experience have worse spatial memory while navigating without such a device. Furthermore, their findings suggest the decline of spatial memory with extensive use of navigation assistance systems.

Research suggests that these problems originate from the need to divide our attention between the navigation system and the environment. Consequently, this permanent back and forth movement impairs spatial memory [19]. Another influencing factor is the degree of automation the system provides. If the human user does not need to pay attention and only passively follows the instructions, it may not acquire as much spatial knowledge as with a lower automation level [20].

While comparing the TBT approach with a paper map, which provides a holistic overview of the area, researchers have found that users of digital aids learned less about their environment than paper map users (e.g., [21,22]). Therefore, many researchers have proposed modifications to the TBT approach to remedy the above-mentioned adverse effects. One approach is to enhance the turning instructions with additional information about landmarks [23] and, in turn, render them more engaging. Providing more contextual information about the environment is another option [2]. Further improvement suggestions include the enhancement with haptic feedback [24]. Instead of modifying the instructions, the environment may be enriched with virtual global landmarks facilitating the orientation [25]. Besides trying to enhance the TBT navigation approach with further information, there are navigation approaches aiming to reduce the overall number of turn-by-turn instructions (e.g., [26]) or avoiding them.

2.2. Alternative Navigation Approaches

The TBT approach has, per definition, a completely predefined route, as turning actions are imposed on the user. Alternatives to this approach give the user more freedom regarding route selection by not using an entirely predefined route.

One of them is the so-called *beeline navigation*, which is based on the *least-angle strategy* [27]. This strategy assumes that users favor options with the least angle with respect to the (believed) destination. Robinson et al. and Dobbelstein et al. implemented this approach by indicating the beeline with vibrotactile feedback [28,29]. Both implementations led participants successfully to the destination while allowing for free movement to explore the experiment area. Savino and colleagues compared TBT with two different variants of beeline navigation for cyclists [30]. One provides only the beeline to the destination, whereas the second provides additional visual cues if the beeline and the shortest path street segment differ. The second approach made participants more confident. For a leisure scenario, participants preferred the beeline approach over TBT.

Another alternative to the traditional TBT approach is the spatial augmentation sound system proposed by Clemenson and colleagues [31]. It acts as an acoustic compass that guides the user towards the destination without explicit instructions. For this reason, audio beacons are employed, which adapt in sound as a function of distance and angle to the user. In a user study, the users of this system pointed more accurately to different destinations than TBT users. This approach was originally developed to help visually impaired individuals. A similar approach was proposed by Albrecht et al. [32].

Haosheng and colleagues proposed *Potential Route Area* (PRA) navigation [33]. The PRA is the area covered by routes no longer than a threshold leading from the current position to the destination. Similarly to our approach, the already walked route is taken into account, but, in contrast to our approach, the environmental spatial abilities are of no importance for this approach. The user is equipped with a digital map highlighting the PRA and landmarks. The idea of this approach is; as long as the user stays within the highlighted area, the destination should be reached within the predefined distance threshold. The area is updated frequently and no instructions are given. The study showed that users of the PRA system draw better sketch maps in terms of route likeness and survey likeness [34] compared to Google Maps participants. Regarding the pointing accuracy to the start point and the number of drawn points of interest in the sketch map, there was no significant difference between both groups.

The *Free Choice Navigation* approach was proposed in our previous work [6]. It aims for more freedom of choice and engagement with the environment while trying not to exceed a maximum route length. The core idea is to provide the user with two pieces of information at the beginning; the beeline direction and distance to the destination. No further information is given to the user before the navigation task starts. As the user moves, the accompanying system tries to predict whether the user needs assistance, i.e., any information that facilitates reaching the destination. This prediction is based on the environmental spatial abilities of the user, the complexity of the upcoming junction and the until now traversed route. The system estimates the user's orientation and spatial confidence based on the user's environmental spatial abilities. With this information, the system can assess whether the user will take a reasonable street segment, given the already walked distance and the maximum allowed distance. If the probability of taking a street segment resulting in a detour above a certain threshold is high or the user is one street segment away from the destination, then a navigation instruction for the upcoming junction is issued. The given assistance can be of any type: visual (screens), auditory (earphones), haptic (vibration motor), etc. The assistance can also be a TBT instruction but does not have to be one. Potentially, it is an indication of the destination, like in the beeline approach. While there is no need for assistance, the user is confronted with the environment, a situation that is expected to support spatial knowledge acquisition [35]. Furthermore, in this situation, the user has to decide which street segment to take. This work presents the first implementation of this navigation approach in a real-world setting. For more details, we refer to the paper that introduces the technical details [6].

3. Research Questions and Hypotheses

In this section, we will present the research questions and justify our hypotheses regarding the outcome of our study. Several research questions result from our previous findings [6] in which we compared Turn-By-Turn (TBT) and Free Choice Navigation (FCN) approaches through a simulation study. All research questions but one, consider the differences between both navigation approaches. The last research question (RQ5) concerns people's willingness to take longer routes if knowledge about the environment or decision freedom is gained. The answer to this question will contribute to the discussion of whether navigation systems should focus on other functionalities than efficiently guiding from a to b, e.g., enhancing spatial knowledge acquisition (e.g., [5]). With our study, we attempt to address the following research questions:

- RQ1: Does the FCN approach lead fewer people (%) to their destination than TBT?
- RQ2: Does the FCN approach lead to fewer navigation instructions than TBT?
- RQ3: Does the FCN approach lead to better spatial knowledge acquisition than TBT?
- RQ4: Does the FCN approach yield longer routes or a higher number of route instructions for users with lower spatial abilities than for users with good spatial abilities?
- RQ5: Are people willing to take longer routes if they gain freedom of choice or learn more about the environment?

The hypotheses and rationales behind the conducted statistical tests are found in Table 1. The tested hypotheses are divided into six groups: effectiveness and efficiency (RQ1 and RQ2), spatial knowledge acquisition (RQ3), spatial abilities in FCN (RQ4), user experience (User Experience Questionnaire (UEQ) [36]), workload (NASA Task Load Index (NASA TLX) Raw [37]), and usability (System Usability Scale (SUS) [38]). RQ5 is not specific to any of the two navigation systems and is, therefore, not considered in Table 1. The tests used to approximate spatial knowledge acquisition are described in Section 4.4.2.

Table 1. An overview of the hypotheses analyzed; column *HG* refers to the group of hypotheses: Eff2 = effectiveness and efficiency, SKA = spatial knowledge acquisition, SA-FCN = spatial abilities in FCN, UEQ = User Experience Questionnaire, NASA = NASA TLX Raw and SUS = System Usability Scale. Column DV presents the subdimension(s) tested. TBT refers to Turn-by-Turn, FCN to Free Choice Navigation and HIGH and LOW to participants with high and low environmental spatial abilities (median split).

HG	DV	Alter. Hypoth.	Rationale
Eff2	Arrival Rate	FCN < TBT	Because of its first implementation and its novelty, we expect a lower arrival rate for the FCN group (in line with our simulation [6])
Eff2	# instructions	FCN < TBT	As FCN is meant to give the user more freedom, i.e., less instructions are expected.
SKA	Judgment of relative direction	FCN < TBT	As in the FCN condition, there is no need to divide the user's attention between a device and the environment, we expect a smaller error.
SKA	Distance Estimation (error)	FCN < TBT	See Judgment of relative direction.
SKA	Abstract Route Drawing	FCN < TBT	The map is visible in the TBT condition map and should help with memorizing turns.
SKA	Route Drawing (Map)	FCN < TBT	We expect TBT users to draw more accurate routes, because they see the route on a map in this condition.
SKA	# Points of Interest	FCN ≠ TBT	On the one hand, FCN users need to actively look around, and on the other, TBT users have a map with POIs, therefore, we expected no difference.
SKA	Points of Interest Configuration Similarity	FCN < TBT	As TBT users see POIs on the map, we expect these to have a higher configuration similarity (bidimensional regression).
SA-FCN	Route length and # instructions	HIGH < LOW	As FCN users have to use their environmental spatial abilities, we expect participants with low self-report sense of direction to perform worse.
UEQ	Attractiveness	FCN > TBT	Due to the novelty of the navigation approach, we expect FCN to be more likeable.
UEQ	Dependability	FCN < TBT	As FCN participants have to partially depend on their environmental spatial abilities, they are more likely to feel uncertain.
UEQ	Stimulation	FCN > TBT	See Attractiveness.
UEQ	Novelty	FCN > TBT	See Attractiveness.
NASA	Mental Demand	FCN > TBT	We expect higher mental demand for FCN users, as they need to rely on their environmental spatial abilities.
NASA	Physical Demand	FCN > TBT	As FCN participants are expected to walk longer routes, we expect higher physical demand for FCN users.
NASA	Temporal Demand	FCN ≠ TBT	As participants in both conditions are instructed to conduct the task at normal pace, we expect no difference.
NASA	Performance	FCN > TBT	See Mental Demand (higher performance score means failure).
NASA	Effort	FCN > TBT	See Mental Demand.
NASA	Frustration	FCN > TBT	Due to the novelty of the wayfinding approach, we expect FCN participants to show an increased level of frustration.
NASA	Overall	FCN > TBT	See Mental Demand.
SUS	Overall	FCN < TBT	We expect the usability of the FCN system to be lower, because of its first implementation and its novelty.

4. Experimental Design

In this section, the experimental design is presented with all its decisions. These include the selection of experiment routes, participants, navigation conditions and the procedure description. The original experimental design was discussed with the Pilot Research Ethics Committee of TU Wien and was improved accordingly. The participants were acquired in two batches. First, friends and acquaintances were asked (snowball sampling). Once this source dried up, more than 2000 emails were sent to PhD students and post-docs of several universities in Vienna. Through these two steps, 50 participants were acquired in total. Two of them were excluded due to language problems (insufficient knowledge of German to understand the experiment task). The participants were not paid, but were offered to participate in a lottery (one prize of EUR 400). Initially, we planned an equal distribution of 26 participants per group, but we had to stop the data collection earlier due to re-emerging COVID-19 restrictions. This resulted in a slightly unequal distribution (FCN = 26, TBT = 22). Assuming $\alpha = 0.05$, effect size = 0.8 (i.e., a large effect), power = 0.8 and equal sample size in both groups, the a priori calculation with the software *G*Power* resulted in a sample size of 21 participants per group. As we expected data loss, we decided to collect a sample of 26 participants per group.

4.1. Data and Software

As the experiment area, the outskirts of Vienna were selected (district Liesing). The outskirts were selected to assure unfamiliarity with the environment. The data needed to build the graph of the experiment area were extracted from OpenStreetMap (OSM) (https://www.openstreetmap.org, last accessed 20 June 2022). The OpenStreetMap data were not completely up-to-date. In consequence, junctions and street segments were added manually. The updated graph had 865 junctions and 1250 street segments and formed the basis to find all possible routes for the experiment using SageMath 9.1 and its SubgraphSearch function (https://doc.sagemath.org/html/en/reference/graphs/sage/graphs/generic_graph_pyx.html, last accessed 30 January 2022). Several junction characteristics (e.g., regularity) were calculated using the Intersections Framework [39]. The remaining characteristics were implemented in Python 3.6.

4.2. Route Selection

We applied our previously developed route selection framework [7] to find suitable routes within the experiment area. In total, three different routes were chosen to decrease potential biases [40]. First, a route population needs to be defined. To limit the number of potential routes, we considered shortest paths only, composed of 18 junctions (according to OSM data) and between 550 and 750 m long. This allows for routes with a reasonable length from a research economics perspective and a sufficient number of junctions, i.e., potential turning points. There were 23,296 potential routes in the experiment area meeting these criteria. The above-mentioned framework finds representative routes for a given area with specific characteristics. The framework ranks routes according to a score that expresses the deviance from an average route given specific categories. The lower the score, the better a route resembles a hypothetical average route in the experiment area. The following five high-level categories with their features were used to calculate the score value for each route [7]:

1. **Segment-length-related features:** (a) average segment length, (b) median segment length, (c) standard deviation of segment lengths, (d) total route length
2. **Cardinality of junctions:** (a) average number of options at junctions, (b) number of n-way junctions (e.g., 3-way and 4-way junctions) along the route
3. **Frequency of turn types:** number of right, left and non-turns along the route
4. **Regularity of junctions:** average angle for n-way-junctions (deviation from a regular n-way junction, for more details see [39])
5. **Point-of-Interest (POI)-related features:** (a) average POI number at junctions, (b) standard deviation of POI number at junctions, (c) average POI uniqueness [41] at junctions, (d) standard deviation of POI uniqueness at junctions, (e) POI per meter along segments, (f) standard deviation of POI per meter along segments

The score calculation can be parameterized in order to reflect the relevance of categories for a given study design. The weights for the five high-level categories were not equal, as the study focuses on spatial knowledge acquisition. Therefore, the presence of points of interest was the most important feature (weight = 0.4). Furthermore, the frequency of turn types was important to avoid prevailing no-turns along the route (weight = 0.3). The remaining three high-level categories, *segment-length-related features*, *cardinality of junctions* and *regularity of junctions* were considered equally important with a weight of 0.1. The high-level category related to points of interest needs further explanation, as there is no agreement about what a point of interest is, and many definitions exist (see [42] for an overview).

4.2.1. Points of Interest

For our experiment, we initially considered every OSM object bearing the amenity tag (e.g., bars, restaurants, churches) as a potential point of interest. After a preliminary analysis and several in situ checks, a few values were excluded from this set because they were not perceivable as points of interest (e.g., rubbish tips and benches). The following values for the key *amenity* were excluded: waste_basket, waste_disposal, recycling, grit_bin and bench. Furthermore, parking-related features were also excluded ("amenity" NOT LIKE '%parking%') because parking places are barely noticeable (Google Street View and in situ check) as fences or shrubs often cover them. The same filtering was applied to polygonal POIs transformed into point features by calculating the polygon's centroid. Moreover, bus stops, downloaded from overpass-turbo (https://overpass-turbo.eu/, last accessed 20 June 2022), were added as points of interest to the data set. Having the POI dataset ready, every POI was snapped to the nearest street segment and to the nearest junction. With this information, the features mentioned above can be calculated. A buffer around junctions or street segments was not used in order to avoid counting POIs more than once and having POIs not assigned to any street segment or junction.

4.2.2. Choosing Final Routes

The flexibility of the framework allows for defining a target route instead of the average one [7]. Given our goals (e.g., having as many POIs as possible), we set certain features of the target route to values different from the average. The number of right, left, and non-turns should be balanced and equal for all three features. Furthermore, the three POI-related features regarding the average (5 a, c and e) were set to the maximum available in the data, as we are interested in having as many POIs as possible. Features regarding the standard deviation (1c, 5 b, d and f) are set to the minimum to have POIs well distributed over street segments/junctions on the route and to avoid very long segments. For all other features, the data mean was used. Based on this target route, the weighted Euclidean distance (aka *score*) between all 23,296 potential routes and this target route was calculated. The smaller the score, the more similar the routes are. Having calculated the score for every potential route, three routes were selected iteratively:

1. Choose the route with the lowest Euclidean distance to target route from the remaining route population (**Step 1**)
2. Check if the route follows a main road only. If yes, exclude it and go to Step 1)
3. Check if the route has enough turning points. If not, exclude it and go to Step 1)
4. Check if the route has enough POIs (Google Street View and in situ checks). If not, exclude it and go to Step 1)
5. Check if the route starts/ends in a dead-end. If yes, exclude it and go to Step 1)
6. Check if the route's start or end point lies in an area accessible only through one street segment, meaning participants will know a part of the route before the actual experiment starts. If yes, exclude it and go to Step 1)
7. Check if the route crosses parking areas. If yes, exclude it and go to Step 1)
8. Check if the route leads through allotments gardens. If yes, exclude it and go to Step 1)
9. Check if the route leads through subways. If yes, exclude it and go to Step 1)
10. Add the route to the final route list
11. Generate two buffers (200 m and 800 m) around all routes in the final route list and create the difference polygon between both buffers. The two buffers are employed to avoid crossing routes and to keep the walking distance between two routes reasonable.

12. Limit the route population to routes within the difference polygon and not intersecting with the smaller buffer
13. Repeat until three routes are found.

The suitability of the three similar (according to the route selection framework) routes was verified in situ before the experiment. One of the three experiment routes was assigned randomly to each participant. The selected routes are presented in Figure 1.

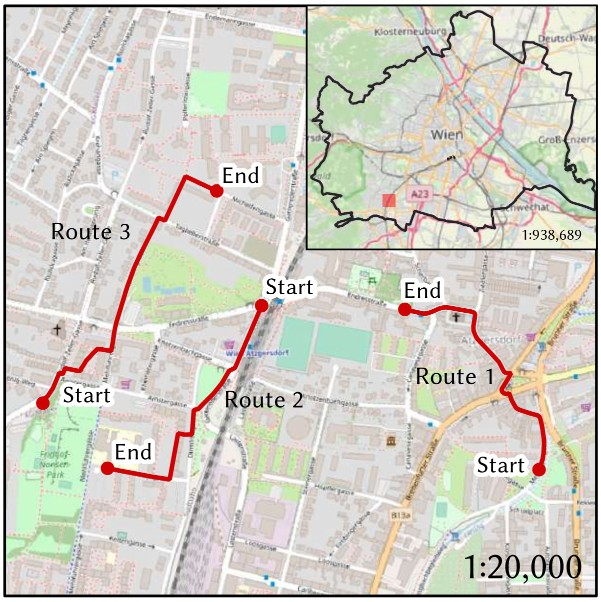


Figure 1. The three final routes in the experiment area located in Liesing (outskirts of Vienna, Austria). The inset map shows the location of the experiment area within the administrative boundary of Vienna. Background map OpenStreetMap.

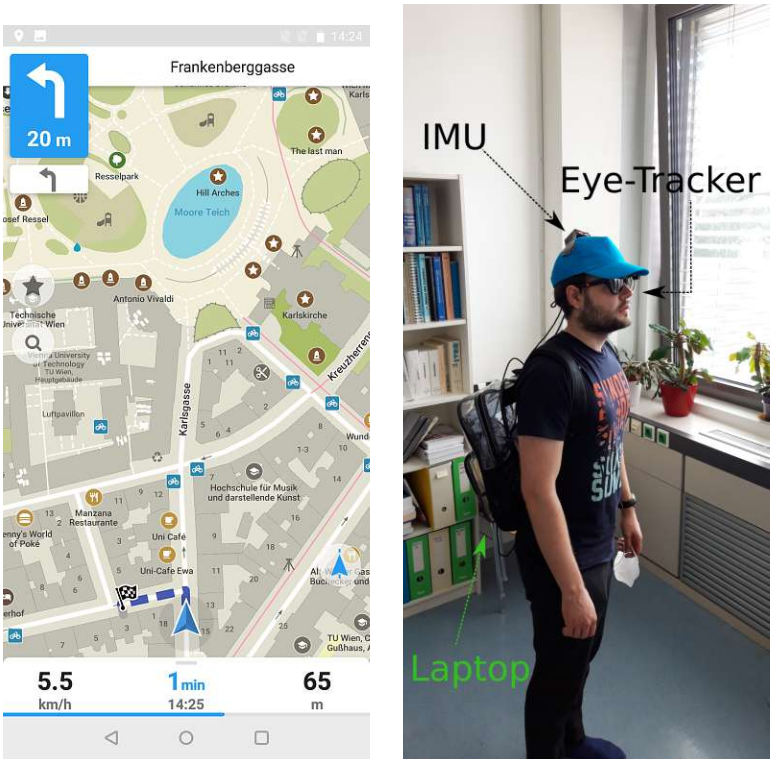
4.3. Conditions

In this subsection, we describe the two navigation conditions (between-subject design), namely Turn-by-Turn (TBT) and Free Choice Navigation (FCN). For safety reasons, all participants were accompanied by the experimenter at all times. While walking, the experimenter logged further data with a custom kotlin app on an Android tablet. In both conditions, the participants received audio instructions via a single Bluetooth earbud (to not block environmental sounds such as cars). The experimenter carried the second earbud. A trial ended once the participant reached the destination within 150% length of the shortest path (success), or it was interrupted if this was not possible anymore due to the walked route so far (failure).

4.3.1. Turn-by-Turn and Application Choice

In the Turn-by-Turn (TBT) approach, an instruction is given at every turning point along a predefined route. A very popular application offering TBT navigation, Google Maps, could not be used because the underlying data are not freely available, and it is different from our data basis in the FCN condition (OSM). Therefore, the navigation systems would not be fully comparable. Several smartphone apps offer OSM-based Turn-by-Turn navigation. However, we excluded many due to shortcomings such as no audio instructions (https://maps.me/, last accessed 22 June 2022), aggressive map matching (https://www.sygic.com/gps-navigation, last accessed 22 June 2022), and uncontrollable intermediate navigation instructions (https://osmand.net/, last accessed 22 June 2022. Finally, the app Organic Maps (https://organicmaps.app/, last accessed 22 June 2022) was chosen, which is similar to MapsMe, but offers audio instructions.

In our scenario, these instructions are issued by the application Organic maps via earbuds. To ensure high positional accuracy, a Global Navigation Satellite System (GNSS) receiver manufactured by PPM (model 10xx-38) was attached to the experiment smartphone (OnePlus 5T) held by the participant. The map orientation changed according to the device orientation (see Figure 2a). The task was to follow the indicated route using the application and its audio instructions.



(**a**) (**b**)

Figure 2. Experiment setup: (**a**) Organic Maps interface with a track-up orientation and 2D buildings; (**b**) Participant with mounted sensors. The laptop powers the IMU (inertial measurement unit) that tracks the participant's head movements. The eye-tracker is used to verify the map drawings of the participants. The pictures do not show the experiment area (illustration purposes only).

4.3.2. Free Choice Navigation

In this condition, the Free Choice Navigation approach [6] was implemented through a custom Android application operated by the experimenter. This approach aims for more freedom while navigating, simultaneously assisting the wayfinder in difficult situations. In the beginning, the participants received two pieces of information: the direction to the destination, marked by a red arrow on the ground, and the beeline distance to the destination. While the participant was walking, the FCN system decided at every junction whether assistance was needed. This decision was based on environmental spatial abilities (derived from the Santa Barbara Sense of Direction Scale (SBSOD) questionnaire), the walked route so far, and the situation at the next junction (e.g., distance to destination, number of options, possible detours).

The task was to find the unknown destination with the assistance of the Free Choice Navigation system. As one of the aims of FCN is minimizing the information provided to the user, the destination was kept unknown, as there was no graphical interface that would have facilitated the communication of the destination. The experimenter stressed that the destination could not be missed because the system would notify the participant on arrival. Furthermore, the experimenter underlined that the destination is a junction and underlined that it is not a point of interest (e.g., church, supermarket, bus stop). While the FCN approach is not tied to any particular method of conveying route instructions, we selected auditory TBT instructions due to comparability with the TBT condition and widespread use (e.g., *"turn left!"*). If the system supported the participant with an instruction, it was valid only for the current junction and not for the upcoming ones (e.g., go straight ahead). Additionally, the instruction *"turn around"* was explained as a 180° turn and a walk back to the previous junction. The participants were asked to follow the issued instructions.

4.4. Procedure

This subsection describes the complete procedure with all its questionnaires and tasks. It consists of an online and an in situ part. The entire experiment, including documents, task descriptions and questionnaires, was conducted in German; however, as there is no official translation of the NASA TLX questionnaire, the original was used, and if needed, an unofficial translation was provided (https://www.keithv.com/software/nasatlx/nasatlx_german.html, last accessed 20 June 2022).

4.4.1. Online Part

The online part started with the experiment description and the informed consent regarding the recorded data. The participants then had to answer questions about demographics (sex and age), usage of navigation aids in unknown environments, spatial strategies (in German Fragebogen Räumliche Strategien [43]), sense of direction (SBSOD) [44] and psychological traits [45]. Furthermore, participants were asked to what degree they would be willing to accept walking longer routes (0–100% longer) for each of the following two reasons: (1) if they would gain more control over the walked route, compared to a predefined route; (2) if they would gain more knowledge about the environment. The completion of the online part took between 15 and 25 min.

4.4.2. In Situ Part

The in situ part took place on the outskirts of Vienna (Austria), in Liesing (see Figure 1). Exclusively persons who visited Liesing no more than once throughout the last year were allowed to participate in order to ensure unfamiliarity. None of the participants was a resident of the experiment area. Before the experiment started, the informed consent was signed, and the assigned condition was explained to the participant. The sensors were then attached to the participant (see Figure 2b). The experimenter explained the task again, and the first trial started if no further questions were left. Once the trial ended (destination reached or not possible anymore to be reached within 150% of the shortest path), the participant filled out three questionnaires regarding the workload (NASA TLX [37]), the usability (System Usability Scale [38]) and the user experience (User Experience Questionnaire [36]). Subsequently, a battery of four tests was used to approximate spatial knowledge acquisition.

First, staying at the destination, the participant was asked to look in the direction of the starting point (judgment of relative direction) and estimate the walked distance. While pointing to the starting point, the experimenter stood 2 m behind the participant and measured the direction with a digital compass app (https://play.google.com/store/apps/details?id=com.vincentlee.compass, last accessed 17 October 2022). The next task was to draw the walked route abstractly (abstract route drawing task). The experimenter stressed that the order and number of turns were important, not metric or absolute information. In this task, participants were also asked to indicate junctions at which they walked straight ahead, i.e., a non-turn. The following two tasks consisted of drawing the walked route and remembered points of interest (POIs) on a map with streets only. The start and end points were also indicated on the map. The experimenter underlined that every remembered detail of the environment could be a POI, e.g., the color or the architectural style of a building, a bus stop or a pedestrian crossing. After the last spatial knowledge acquisition task, the participant conducted an additional task about wayfinders' orientation. These data were collected in the same study to minimize the number of rides to the experimental area and to reduce time effort considerably. As this additional task always took place after the navigation task with TBT or FCN, it did not influence the study results and is thus irrelevant to this work.

After a short debriefing, participants were allowed to ask questions regarding the experiment and the research questions. If no questions were left, the experiment ended at this point. The completion of the in situ part took between 90 and 120 min.

5. POIs—Data Cleaning

The participants had to draw POIs on a map. In order to analyze them, data cleaning was needed. While we excluded overly generic entries (e.g., "building"), POIs referring to specific details (e.g., "yellow building") were considered. Points, lines, and polygons were valid shapes for a POI. We additionally excluded entities not located along the route or visible from a distance, which participants likely knew due to their way to the experiment. Furthermore, we considered non-permanent objects [46,47] such as a parked yellow motorbike or temporary placed furniture on the sidewalk as valid POIs for the analysis, since they represent a memorized detail of the environment. To obtain real-world coordinates of the POIs, the paper map with the marked POIs was georeferenced with QGIS 3.14 [48] to match the OSM map. If the drawn POI was not present in the OSM map, the eye tracking video was used to extract the position (potentially missing features in OSM). If the POI was not present on the map and no video was available, then the location derived was based on the experimenter's memory. If the drawn POI was found neither on the map nor in the video (or experimenter's memory), it was excluded from the analysis. Polygon-like features were only valid if delineated completely (e.g., park and public swimming pool). To convert valid polygons and lines (e.g., railway lines) into point features, their centroid was used.

6. Analysis and Results

In this section, we present the study results regarding our research questions and hypotheses (see Section 3). If not stated otherwise, the number of participants equals 48 (FCN—26 (10 females), TBT—22 (10 Females)). Given that there are potentially large individual differences [49,50] in spatial abilities, we compare the answers (SBSOD questionnaire) of both groups in order to ensure that any significant difference will not originate from differences in environmental spatial abilities. A Wilcoxon–Mann–Whitney test did not show a significant difference ($Z = -1.37$, $p = 0.17$) between the FCN ($M = 0.58$, $SD = 0.12$) and the TBT ($M = 0.64$, $SD = 0.17$) groups regarding self-reported spatial abilities (scaled to the interval [0;1]). As OSM was used as the underlying data, the walked and drawn routes were snapped to the OSM network before the analysis. We analyzed (Data analysis was conducted using GNU R v4.2.1 and its packages dplyr v1.0.9 [51], stringr v1.4.0 [52], coin v1.4.2 [53], tidyr v1.2.0 [54], Cairo v1.6.0 [55], ggplot2 v3.3.6 [56], stringdist v0.9.8 [57], SimilarityMeasures v1.4 [58], geojsonR v1.1.0 [59], BiDimRegression v2.0.1 [60].) the resulting dataset with respect to six groups of hypotheses (see Table 1). For all statistical tests, we used Wilcoxon–Mann–Whitney tests due to the non-normality of the data (Shapiro–Wilk tests and Q-Q plots). In order to avoid inflation of α-errors, we applied corrections to the p-value according to Holm [61] (baseline $\alpha = 0.05$).

Besides comparing the two navigation systems, we analyze people's general willingness to take longer routes. Finally, we scrutinize the impact of environmental spatial abilities (SBSOD, median split) on route length and the number of received instructions in the case of the FCN condition (see Section 3 and Table 1).

6.1. Arrival Rate and Number of Instructions

All participants (22) in the TBT condition reached the destination, whereas, in the FCN condition, 23 out of 26 (88.46%) participants were successful. Next, we compare the relative (normalized by the number of traversed junctions) and the absolute number of received instructions. We consider the relative number of instructions because FCN users should traverse more junctions, given their freedom. With the FCN ($M = 0.4$, $SD = 0.15$) approach, participants had significantly fewer ($Z = -3.18$, $p < 0.001$) instructions than the TBT group ($M = 0.56$, $SD = 0.11$), relative to the number of traversed junctions. Regarding the absolute number of instructions, there was no significant difference ($Z = -2.15$, $p = 0.016$—Holm correction) between both groups (TBT: $M = 6.95$, $SD = 1.29$; FCN: $M = 5.88$, $SD = 2.36$).

6.2. Spatial Knowledge Acquisition

In this subsection, we present the results regarding spatial knowledge acquisition: judgment of relative direction (JRD), walked distance estimation, abstract route drawing, route drawing on a map, and drawing points of interest on a map (see Section 4.4.2 for details on tasks).

6.2.1. Pointing to Start Point and Distance Estimation

For both tasks, we calculated the absolute deviation of the estimation from the true value (i.e., under- and overestimation were considered equally). There was no significant difference ($Z = 0.25$, $p = 0.803$) between FCN ($M = 24.5°$, $SD = 27.88°$) and TBT ($M = 17.95°$, $SD = 14.09°$) regarding the JRD task. For the distance estimation task, the sample size is 44 (26 FCN, 18 TBT) because 4 participants in the TBT condition saw the walking distance at the beginning of the navigation task. The rest was not aware of the walking distance. Regarding the estimation of the walked distance, there was no significant difference ($Z = -2.13$, $p = 0.017$—Holm correction) between both groups (TBT: $M = 252.67m$, $SD = 282.36m$; FCN: $M = 135.35m$, $SD = 121.53m$).

6.2.2. Abstract Route Drawing

Having collected the data, we found that the concept of a junction varies considerably among participants (see potential future work in Section 9). Therefore, we only analyze turns but do not consider drawn junctions at which the route was continued (no turn). First, we compare the number of turns drawn with the actual number of turning points during the trial (absolute value). There was no significant difference ($Z = 0.230$, $p = 0.815$) between the FCN ($M = 1.28$, $SD = 1.43$) and the TBT ($M = 1.23$, $SD = 1.45$) groups regarding the number of drawn turns compared to these actually walked. Second, we compare the sequence of turns (right, left, and turn around) with the walked sequence using the Levenshtein distance, a widespread measure in natural language processing successfully employed to compare route sequences in [62]. One drawing from the FCN condition was excluded, because the turning points were not appropriately marked with letters (R—right, L—left) ($n = 47$). Again, there was no significant difference ($Z = -0.19$, $p = 0.852$) regarding the Levenshtein distance between the walked turn sequence and the drawn one between FCN ($M = 1.52$, $SD = 1.48$) and TBT ($M = 1.59$, $SD = 1.47$).

6.2.3. Route Drawing on Map

A route similarity metric is needed to compare the walked route with the drawn one on a map. As the drawn trajectories do not have a temporal component, we will not consider similarity measures accounting for the temporal data dimension [63]. Toohey and Duckham compared four similarity measures for routes and provided an R package for the calculations [64]. The four compared measures are: Fréchet distance (FD), dynamic time warping (DTW), longest common subsequence (LCSS) and edit distance on real sequence (EDR). We exclude the Fréchet distance because back and forth movements are not allowed in this similarity measure [64], but several participants walked a street segment twice. From the four mentioned measures, Su and colleagues [63] found that DTW and LCSS can handle different types of transformations, whereas EDR and FD do not. According to Tao and colleagues [65], DTW and FD were more in line with their human expectations while conducting a series of tests (e.g., bird routes). As we already mentioned, we excluded FD and, in consequence, compared the walked routes with the drawn routes on a map with DTW. The lower the DTW score, the more similar both trajectories are. There was no significant difference ($Z = 2.67$, $p = 0.004$—Holm correction) between the FCN ($M = 572.19$, $SD = 797.36$) and the TBT ($M = 375.32$, $SD = 1281.52$) groups regarding the DTW score between drawn and actually walked routes.

6.2.4. Points of Interest on Map

Regarding points of interest (POIs) drawn by participants, we analyze the absolute number and the configuration similarity applying bidimensional regression. There was no significant difference ($Z = -1.25$, $p = 0.211$) between the FCN ($M = 5.88$, $SD = 1.83$) and the TBT ($M = 7.59$, $SD = 3.69$) groups regarding the number of drawn POIs on the map. We applied bidimensional regression, proposed by Tobler [66], to assess the configuration similarity between the drawn POIs and their true locations. We use the R package *bidimregression* [67], which builds on Friedman's work [68] and offers as well significance tests proposed by Nakaya [69]. To calculate any statistics, at least 4 pairs of coordinates are needed [69], therefore, we consider only participants with at least 4 valid (see Section 5) drawn POIs, i.e., we base our analysis on $n = 42$ participants (FCN = 23, TBT = 19). For each valid (at least four valid POIs) participant, the R^2 coefficient was calculated. The R^2 coefficient expresses the configuration similarity between the drawn POIs and their true locations. A Wilcoxon-Mann–Whitney test did not reveal a significant difference ($Z = -0.8$, $p = 0.426$) regarding the configuration similarity between FCN ($M = 0.87$, $SD = 0.22$) and TBT ($M = 0.9$, $SD = 0.22$).

6.3. Workload and User Experience

In this subsection, we will analyze the differences between FCN and TBT regarding user experience (UEQ), workload (NASA TLX Raw) and usability (SUS) (see Table 1).

6.3.1. SUS

One missing value in the System Usability Scale questionnaire was replaced with the most frequent answer (mode) for the affected question [70]. Between FCN ($M = 83.94$, $SD = 8.89$) and TBT ($M = 81.02$, $SD = 12.69$) there was no significant difference found ($Z = 0.56$, $p = 0.574$). Both navigation systems fall into the second-highest category "A" in the Sauro–Lewis SUS curved grading scale [71].

6.3.2. UEQ

In total, two of the six subdimensions, *perspicuity* and *efficiency*, will not be analyzed because questions 21 and 23 were not answered in the FCN condition, as no graphical interface was present. In total, five values were missing, which were replaced by the mode (see, again, [70]). We used the analysis tool [72] provided by the authors to assess the hedonic quality (stimulation and novelty) of both systems. FCN has a very high hedonic quality (excellent stimulation and good novelty), whereas the TBT approach provides a below average hedonic quality (below average stimulation and bad novelty). A series of Wilcoxon–Mann–Whitney tests showed significantly better results for FCN for the subdimensions stimulation and novelty (see Table 2). The subdimensions attractiveness and dependability did not show a significant difference.

Table 2. Inferential statistics for the User Experience Questionnaire. Significant results are boldfaced. FCN refers to the Free Choice Navigation condition and TBT to the Turn-by-Turn condition. The subdimensions *perspicuity* and *efficiency* are left out due to missing data.

Dimension	*p*-Value	Z-Value	Alter. Hypoth.
Attractiveness	0.014	2.21	FCN > TBT
Dependability	0.301	−0.52	FCN < TBT
Stimulation	**0.001**	**3.07**	FCN > TBT
Novelty	**<0.001**	**4.66**	FCN > TBT

6.3.3. NASA TLX Raw

There was no significant difference ($Z = 2.52$, $p = 0.006$—Holm correction) in reported *mental demand* between FCN participants ($M = 8, SD = 4.35$) and TBT users ($M = 5.32$, $SD = 3.24$). The remaining subdimensions of the NASA TLX questionnaire did not reveal significant results either (see Figure 3 and Table 3). Additionally, no significant difference concerning the overall task load (sum) was found between both wayfinding methods.

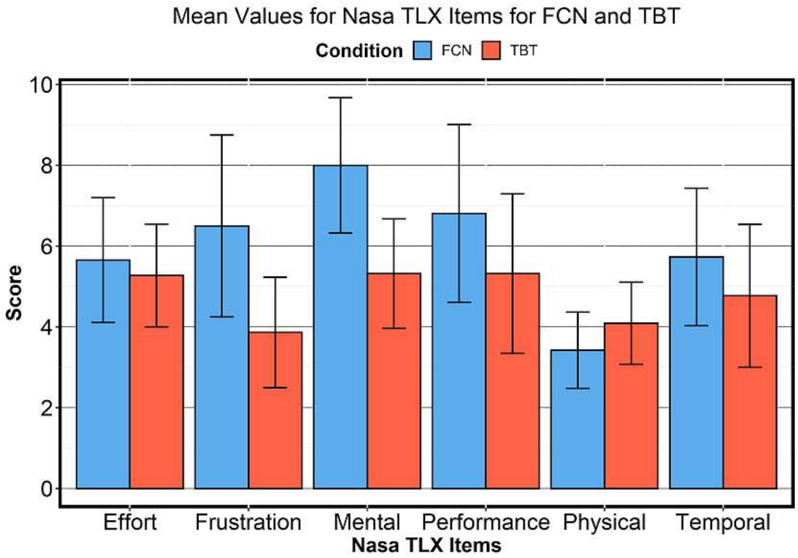


Figure 3. Mean values for NASA TLX Raw items for FCN (blue) and TBT (brick), error bars represent 95% confidence intervals.

Table 3. Inferential statistics for the NASA TLX Raw comparison. FCN refers to the Free Choice Navigation condition and TBT to the Turn-by-Turn condition.

Dimension	*p*-Value	Z-Value	Alter. Hypoth.
Mental Demand	0.006	2.52	FCN > TBT
Physical demand	0.853	−1.05	FCN > TBT
Temporal demand	0.427	0.79	FCN ≠ TBT
Effort	0.492	0.02	FCN > TBT
Performance	0.168	0.96	FCN > TBT
Frustration	0.074	1.44	FCN > TBT
Sum	0.075	1.44	FCN > TBT

6.4. A Wish for Freedom and Learning

In the online part of the study, all potential participants were asked about the increase in route length (in %) they would accept if they (1) gain more control over the route (in contrast to a predefined route) or (2) learn more about the environment. These answers will shed light on whether subjects would value wayfinding assistance not based on shortest-path guidance. As these are general questions, which are condition independent, they were asked before the experiment to avoid potential bias. In total, 81 potential participants finished the online part (48 signed up for and finished the in situ part) and replied to both questions. The answers show an interest in having more freedom while navigating and/or learning about the surrounding environment (see Figure 4). A paired Wilcoxon test showed that participants have a preference for longer routes ($V = 251$, $p < 0.001$) in order to learn more about the environment ($M = 61.41\%$, $SD = 30.23\%$) rather than accepting longer routes to gain control over the route ($M = 48.27\%$, $SD = 30.65\%$).

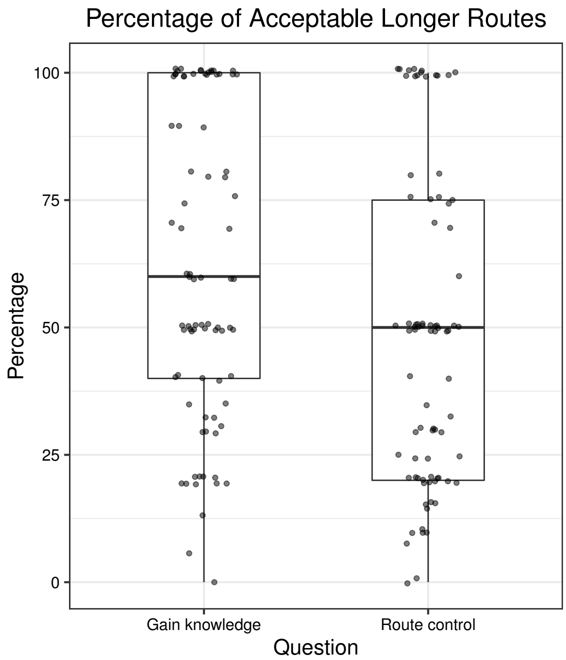


Figure 4. Boxplots with jittered data points of longer routes (%) participants are willing to take to have more (1) control over the walked route or (2) knowledge about the environment.

6.5. Environmental Spatial Abilities and Performance in FCN

In this subsection, we scrutinize whether self-report environmental spatial abilities (SBSOD) impacted the performance in the FCN condition. As a proxy for the performance, we will consider route length, the absolute number of instructions and the relative number of instructions (normalized by the number of traversed junctions). The arrival rate would be a performance indicator, but there were not enough participants who did not finish the trial successfully. As the three routes have different lengths, the walking distance of each participant is normalized by the shortest path length of the corresponding route. The 23 successful participants in the condition FCN were split into two groups regarding their environmental spatial abilities (median split into groups *low* and *high*). No significant difference was found ($Z = -0.28$, $p = 0.782$) between participants with low ($M = 1.18$, $SD = 0.14$, $n = 12$) and high ($M = 1.21$, $SD = 0.19$, $n = 11$) environmental spatial abilities. Additionally, there was no difference found regarding the absolute ($Z = 0.56$, $p = 0.58$) nor the relative ($Z = -0.03$, $p = 0.98$) number of instructions.

Taken together, our analyses reveal: (1) Participants assigned to the FCN condition received fewer instructions (normalized by the number of traversed junctions) than those using the TBT system; (2) There was no significant difference between both groups in terms of spatial knowledge acquisition; (3) The FCN navigation system was rated higher in terms of stimulation and novelty (UEQ); (4) As a reason for walking longer routes, learning more about the environment is preferred over controlling the exact route.

7. Discussion

The rationale behind FCN is to provide users more freedom to make route decisions while navigating. As the decision-making process about which street segment to take is not fully outsourced to the navigation system (as in TBT), we expected more engagement and interaction with the environment and, consequently, increased spatial knowledge acquisition.

The most important capability of a navigation system is to successfully guide users to their destinations. Regarding the arrival rate (**RQ1**), the FCN approach (arrival rate 88.46%, 23/26 participants) is less effective than the TBT approach (arrival rate 100%). The superiority of TBT over FCN, regarding the arrival rate, is in line with our previous simulation study [6]. One participant did not interpret the given navigation instruction correctly and took a wrong turn. In the case of two further participants, our system did not give any instruction at a junction because, according to our model [6], the participants were still well oriented, but apparently they were not and took the wrong street segment, i.e., the actual participant's knowledge about the direction towards the destination (belief vector) and the modeled one did not correspond, and an instruction should have been issued at this junction. Although the modeled belief vector works reasonably well most of the time, it requires further revision and improvement (discussed in Section 9).

On the other hand, FCN succeeded in giving more freedom to the user (**RQ2**). FCN participants had to make their own decisions at more than 50% of the traversed junctions, which is, again, in line with our previous work [6]. Not only did the users have to make their own decisions at several junctions, they were also provided with fewer instructions relative to the number of traversed junctions. Furthermore, less navigation system use favors more forward and backward glances [73], and, therefore, the environment is potentially observed more attentively. Parush and colleagues concluded that forcing participants to engage with the environment can lead to better spatial knowledge [74]. In consequence, we hypothesized that users would direct this attention to the environment and, in doing so, enhance their spatial knowledge acquisition (**RQ3**). The collected data do not support this hypothesis. We did not find a significant difference between the two systems for any of the spatial knowledge acquisition tasks. Although there was no significant difference regarding SKA, we want to highlight some tasks. FCN participants estimated the walked distance on average better by ca. 115 m than TBT participants, which suggests the value of FCN for proprioception. TBT users traced their route on a map more accurately than FCN participants. This was expected because a map was always visible during the trial. While we hypothesized that the presence of the map with the route (TBT) would facilitate memorizing the turns, no difference between both conditions was found. Perhaps TBT participants did not often look at the map. This can be answered with the eye-tracking data collected but not yet analyzed (see Section 9). Regarding the number of drawn POIs, we expected no difference as TBT users had a map with POIs, and the FCN users had to actively look around and remain attentive while navigating. TBT participants drew on average 1.7 POIs more (insignificant difference like in [33]) suggesting that forced engagement with the environment might be insufficient grounds to improve landmark memory, which is in contrast to the work by Parush and colleagues [74] suggesting that keeping users attentive may lead to better spatial knowledge. Both groups had a similarly high configuration similarity of the drawn POIs. This was unexpected, as FCN users had no map to see the POIs put into relation. This is of particular interest and suggests that people can compensate for a missing map that provides this type of information. Regarding the JRD task, our data did not reveal any difference between both systems. This is in line with [33], but in contrast to [31], although in both works participants had the freedom to choose their own routes. Therefore, more analysis is needed to understand where this difference potentially originates from.

The missing improvement in spatial knowledge has several potential reasons: (1) The users need more support, e.g., a map display on demand [74], although other results suggest that audio-only instructions can lead to comparable spatial knowledge acquisition such as smartphone or AR-based navigation [8]; (2) The users may also need information between junctions to improve orientation and trust [75]; (3) The user needs more time to familiarize with the FCN navigation approach to have more trust in the system; (4) Making own decisions does not guarantee enhanced spatial knowledge acquisition, although it has the potential to do so [33]; (5) Making own decisions does not mean full engagement with the environment and looking around in all directions [73]. It is also possible that the participants were only attentive around the junctions but not in between.

There was no significant difference regarding the workload (NASA TLX Raw). Contrary to our expectations, FCN participants did not report a significantly higher mental demand than TBT participants. This would be in line with the work of Haosheng and colleagues [33], in which participants also had to make their own decisions at junctions.

According to the NASA TLX results, FCN participants did not feel an increased physical demand—despite an average increase in route length of 19%. This suggests that moderately increased walking distances (in the FCN condition on average 19%, compared to the shortest path) can be used for further purposes without increasing the physical demand considerably. This is in line with people's willingness to take longer routes (see Section 6.4). We also expected that FCN participants would experience increased levels of effort, frustration, and performance (the higher, the greater the sense of failure), but the data did not reveal significant differences with respect to TBT. In order to explain these results, further work with interviews after the trial is needed to obtain more in-depth information about the users' perception of the system. According to our expectations (see Table 1), the FCN system was rated higher regarding attractiveness, novelty, and stimulation (UEQ). A high score in stimulation shows that our system is motivating. Although we predicted a lower score for dependability in the FCN condition because of the uncertainty if an instruction will be given at the next junction, the dependability of the two navigation systems did not differ. This outcome suggests that, although FCN users did not know the exact mechanism behind the system, they did not feel less secure than TBT users. On the other hand, the dependability of Organic Maps is possibly lower than in the case of Google Maps, to which most users are accustomed to. Regarding the usability (SUS), both systems did not show any difference; however, both systems have potential for improvement as they fall into the second-highest category "A" in the Sauro–Lewis SUS curved grading scale [71] and not into the highest one. Therefore, we conclude that the FCN navigation system demonstrates an acceptable performance regarding user experience and usability.

In our previous work [6], we hypothesized that FCN would be more difficult for users with low environmental spatial abilities (**RQ4**). The arrival rate would be one indicator, but there was not enough data, i.e., there were not enough participants that did not finish the trial successfully. Another proxy can be the length of the walked route and the number of received instructions. Longer routes would indicate more difficulties in reaching the destination, and an increased number of instructions would indicate more assistance by the system and less independent navigation. As no difference was identified regarding these two features, we cannot conclude that people with low environmental spatial abilities experience more difficulties than those with high environmental spatial abilities while using Free Choice Navigation. This is not in line with our previous simulation results [6] in which agents with lower environmental spatial abilities reached their destination less often. One possible explanation is that our simulation did not model spatial cognition profoundly.

The online survey on the willingness to take longer routes (**RQ5**) showed that learning about the environment is more desirable than gaining control over the route as a reason for taking longer routes (see Figure 4). As the average answer to the question about learning the environment was 61%, it suggests that people are interested in becoming more familiar with and gaining more knowledge about their environments. This is an argument in favor of works on navigation systems enhancing spatial knowledge acquisition, as long as this aspect is an add-on to an acceptable arrival rate.

Taken together, we have seen the potential of Free Choice Navigation to provide wayfinders more freedom while navigating. This might also increase serendipity effects (e.g., they encounter new features in the environment). Based on informal post-experiment conversations, we have the impression that our approach can be combined with gamification: Several FCN participants expressed that they liked the approach because it felt akin to a scavenger hunt. Similarly, creativity during wayfinding might be stimulated as one participant claimed to have oriented herself based on a specific cloud, albeit the person had no experience in orienteering sports.

8. Limitations

Several limitations apply to our work. The first aspect relates to the point in time at which participants received the instruction to turn around. Having made a decision leading to such a "go back" instruction, users are only informed about this wrong decision at the upcoming junction in the current implementation. An updated implementation could, for example, notify users shortly after the junction at which such a decision was made. This would save walking distance and probably increase the number of successful participants in the FCN condition. We did not implement this improvement in order to keep the results comparable with the simulation study [6]. The modeling of the environmental complexity for a junction influences the FCN navigation approach, as a higher environmental complexity leads, broadly speaking, to more difficulties in taking an appropriate street segment according to our model [6]. Therefore, further modeling approaches (e.g., [76,77]) need to be tested because we believe that a more realistic measure for environmental complexity would improve the FCN approach, as difficult junctions could be identified better and the system would assist the user more accurately. Regarding the analysis of the TBT approach, one limitation is that we did not control which points of interest were visible at which zoom level. This selection, determined by Organic Maps, may have had an impact on the acquisition of spatial knowledge. Having said this, while participants could have changed the zoom level, the majority of participants did not change it at all.

As people were unfamiliar with the concept of FCN and there was no graphical display, their trust in the system was somewhat limited. Therefore, a longitudinal navigation study seems to be a better choice to familiarize users with the FCN approach, potentially increase their trust in the system [78] and meet pedestrian needs [79].

9. Conclusions and Future Work

In this study, we implemented a first prototype of the *Free Choice Navigation* (FCN) approach and compared it with the widespread Turn-by-Turn (TBT) approach. The study showed that participants can be guided successfully to their destinations and, at the same time, receive fewer navigation instructions in comparison with the TBT approach (relative to the number of traversed junctions). Fewer instructions and forced engagement with the environment, however, did not result in differences with respect to spatial knowledge acquisition, but it is worth mentioning that FCN users (without a map) can extract spatial configuration information as well as TBT users equipped with a map. Moreover, we provided evidence that people are interested in learning more about their environments and are willing to walk longer routes to achieve it. Finally, we present the first real-world use of the route selection framework [7], which can guide researchers having to select one or more routes between several thousand ones. Regarding future work, there are several potential directions to follow.

The FCN approach can be further improved by implementing turn-around instructions to avoid unnecessary detours. The collected data allows for updating several assumptions we made in the initial model [6], making the model more accurate. Notably, the additional task in which participants had to conduct several pointing tasks is valuable for improving the belief vector [6] in our model. In this study, auditory TBT instructions were used. In further studies, other types such as smartphone-based instructions, augmented reality cues [4,80] or vibrotactile feedback [28] could be used to convey useful information at junctions if assistance is needed. The head-mounted augmented reality approach seems to be the most promising one, as the user does not need to look at an additional screen. Furthermore, the destination can be made always visible (beeline approach), as geographic objects can be visualized quite accurately outdoors [81]. If auditory instructions are used again, they can be altered by adding additional information [2,82]. Instead of dividing the environment at junctions, spatial chunking [83] could further decrease the number of instructions issued. Furthermore, the prediction mechanism behind FCN can be combined with the conceptual framework of Jin and colleagues [84] to better model route choice behavior.

Another interesting research question regards the perception of junctions by users, as we observed different notions among participants. Not all junctions identified by the underlying OSM data were perceived as such. Another example is a roundabout, which can be considered one 5-way junction or five 3-way junctions. Therefore, a human-subject experiment will scrutinize the perception of junctions.

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Abbreviations

List of Abbreviations

AR	Augmented Reality
FCN	Free Choice Navigation
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
JRD	Judgment of Relative Direction
NASA TLX	NASA Task Load Index
OSM	Open Street Map
POI	Point of Interest
PRA	Potential Route Area
Q-Q Plot	Quantile-Quantile Plot
QGIS	Quantum Geographic Information System
RQ	Research Question
SBSOD	Santa Barbara Sense of Direction Scale
SKA	Spatial Knowledge Acquisition
SUS	System Usability Scale
TBT	Turn-by-Turn
UEQ	User Experience Questionnaire

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CHAPTER 8

BeeAR: Augmented Reality Beeline Navigation for Spatial Knowledge Acquisition

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Author's Contribution: conceptualization, methodology, formal analysis, investigation, data curation, writing — original draft preparation, writing — review and editing, visualization.

BeeAR: Augmented Reality Beeline Navigation for Spatial Knowledge Acquisition

BARTOSZ MAZURKIEWICZ, MARCELO L. GALVÃO, and IOANNIS GIANNOPOULOS, TU Wien, Research Division Geoinformation, Austria

Fig. 1. BeeAR Navigation overlays the destination with a digital landmark permanently visible to the user. While approaching the destination, the digital landmark appears bigger. The participant is closer to the destination in the middle photo than in the left photo. The participant wears a Microsoft Hololens 2.

Navigation assistance systems have become integral to our daily routines, helping us to find our way through unfamiliar environments. However, their use may come at a price, as empirical evidence suggests a potentially harmful impact of these systems on our spatial abilities, including the acquisition of spatial knowledge. This could be remedied by giving users more freedom and involving them in the decision-making process. Therefore, we present a navigation system that combines augmented reality and Beeline Navigation (BeeAR). Here, the location of the destination is overlaid with a digital landmark and permanently displayed to the user via a visual, translucent AR display (without a map). Since the digital content is integrated into the real world, no mapping between the device and reality is required, potentially lowering the workload. Making one's own decisions along the route is expected to increase engagement with the environment, leading to increased acquisition of spatial knowledge. We compare BeeAR with findings from a previous study comparing Free Choice Navigation (FCN) and Turn-by-Turn (TBT) navigation conducted along the same routes on the outskirts of Vienna, Austria. Although BeeAR and FCN do not provide users with a map, BeeAR users could better retrace the walked route and remembered more points of interest along the route than FCN users. Participants of all three navigation conditions achieved a high configuration similarity between drawn points of interest and their true locations, albeit only one navigation condition included a map.

CCS Concepts: • **Information systems → Geographic information systems**; **Location based services**; **Decision support systems**; • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; • **Computing methodologies → Mixed / augmented reality**.

Additional Key Words and Phrases: beeline navigation, augmented reality, spatial knowledge acquisition

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1 INTRODUCTION

Navigation is an everyday task and part of the daily routine of billions of people. Nowadays, an increasing number of users use their smartphones to get to their desired destinations. Usually, the user receives a sequence of turning instructions leading to the destination. This type of navigation is known as *Turn-by-Turn* (TBT) navigation, and there is empirical evidence of a negative impact of this navigation approach on spatial cognition (e.g., [9, 24]). The prevention and mitigation of these effects is the subject of current research (e.g., [30, 38]). Therefore, we propose a novel navigation approach based on head-mounted augmented reality (AR). Our AR-based system displays the destination at the exact geographic location and leaves all decisions along the route to the user. As own decisions must be made, the user is expected to engage more with the environment as opposed to a predefined route provided by TBT-based navigation systems. Unlike the classic beeline approach in which the user follows a compass, there is no need to map any information from a device to the environment, as the relevant information, the destination, is displayed as part of reality. This potentially lowers the mental workload [47]. Since there is no additional screen to look at, the user can potentially walk without interruptions to retrieve relevant information.

The focus of this work is to present the strengths and weaknesses of our novel augmented reality-based navigation system by comparing it with two navigation systems: (1) the popular TBT navigation; (2) the Free Choice Navigation (FCN), which was actually the inspiration for the approach presented in this paper. In order to make this comparison, we needed to conduct a further user study to collect data for BeeAR, as experimental results for the TBT and the FCN approaches are already available [45]. We conducted a user study with 16 participants navigating with our novel navigation system in a real-world environment, performing the exact same procedure in the same environment as the other two systems being compared. In total, including the data from the previous study, 48 participants navigated with one of the three navigation systems (BeeAR: 16, FCN: 16, TBT: 16). The differences between TBT and FCN will not be discussed further, as they have already been published [45]. The contribution of this work is fourfold:

(1) We present data showing that BeeAR users have high configuration knowledge of the environment despite no map being provided;
(2) We provide empirical evidence that BeeAR participants are better at retracing their walked routes than FCN participants, despite no map being provided in either navigation condition;
(3) We show that BeeAR participants remember (and draw) more points of interest than FCN participants;
(4) We present data indicating very good usability (System Usability Scale [2]) of the BeeAR navigation system.

2 RELATED WORK

This section discusses two strands of related work. First, we will discuss different navigation approaches and, if applicable, their influence on spatial knowledge acquisition. Second, we will review navigation systems based on augmented reality.

2.1 Navigation Approaches

This subsection presents different approaches how to guide users to the desired destination. Differences can originate from the used modality (e.g., audio vs. vibrotactile) or the concept behind the navigation (communicating turn instructions vs. indicating the destination direction).

2.1.1 Turn-by-Turn Navigation. The *Turn-by-Turn* (TBT) approach guides the user to the destination through a sequence of turning instructions. Usually, this instruction is issued just before the turn maneuver takes place. The most prominent navigation system implementing this approach is Google Maps, used by pedestrians, car drivers and cyclists. The turning instruction can be provided in many forms, e.g., mobile maps [37], augmented reality cues [27] and audio instructions [68]. Furthermore, the HCI community proposed systems using sensory channels other than our eyes and ears. The system proposed by [19] vibrates if the user is looking at the right branch. The public infrastructure can also be used to convey turning instructions (e.g., [6]). This navigation approach is effective in guiding users to their desired destination, however, there is empirical evidence suggesting that this type of navigation is negatively affecting spatial cognition.

Krüger and colleagues [32] investigated the influence of TBT instructions on spatial knowledge acquisition and concluded that this navigation type helps to build up landmark knowledge but is not favorable to survey knowledge. The experiment of Hejtmánek and colleagues [24] showed that increased map time usage lowers the accuracy of the acquired knowledge in a virtual environment. A second trial (without an assistance system) showed that participants spending more time with the map during the first trial walked longer routes. People with more accumulated experience with navigation systems are more likely to stop more frequently, take longer routes [28], and miss landmarks in their environment [9] while navigating without assistance. This last finding is in line with the work of Ruginski and colleagues [56], who found an indirect negative effect of GPS usage on environmental learning. These potentially negative effects on spatial cognition are attributed to not focusing on the environment, as the navigation system requires the user to switch attention between the system and the environment [17, 40]. The automation level of these systems may also play a role, as the user can passively follow the instructions while reaching the destination [3]. Given these potential drawbacks, TBT modifications have been proposed. The turning instructions can be enriched with extra information about the environment [60, 67] or their absolute number can be reduced by navigating simpler routes [12]. These approaches still require the user to follow a predefined route.

2.1.2 Alternative Navigation Approaches. Involving the user in the path planning process (previous to navigation) can improve survey knowledge and self-orientation [40]. Therefore, it is reasonable to give the user more freedom and integrate it into the decision-making process along the route. In consequence, the discussed alternatives share the property of not imposing a predefined route on the user.

The so-called *beeline navigation* is one alternative to the TBT approach. It uses the compass metaphor by conveying the direction to the destination without indicating which branch to take next. The direction to the destination can be encoded visually, auditory or vibrotactile, among others. Savino and colleagues [59] compared the beeline approach with TBT in a user study involving cyclists. The direction to the destination was conveyed visually on a device attached to the handlebar. No difference between both groups was determined regarding the pointing to the start point task. However, TBT users took shorter routes, committed fewer navigation errors and reported a lower task load. The works of [10, 55] are examples of encoding the destination direction in a vibrotactile manner. They were not compared to the TBT approach, but the user studies showed that the shortest path is not necessarily taken with this navigation approach. Clemenson and colleagues [5] proposed an acoustic beeline approach in which audio beacons convey distance and direction information. For participants new to the experimental area, this system led to better performance while pointing to different places in comparison to TBT participants.

Another navigation system that leaves all navigation decisions to the user is the *Potential Route Area* (PRA) navigation approach proposed by Huang and colleagues [26]. This highlighted area encompasses all possible routes from the current location to the destination not longer than a predefined threshold. A user study comparing this approach with Google Maps revealed that PRA users draw more accurate sketch maps considering survey likeness and route likeness [33]. The number of drawn points of interest in the sketch map and the accuracy in the pointing task did not differ significantly.

The *Free Choice Navigation* (FCN) approach was proposed in our previous work [45] and supports the user with occasional turning instructions. Whether the navigation system issues a navigation instruction at the current junction is decided based on the user's environmental spatial abilities (approximated with the Santa Barbara Sense of Direction Scale (SBSOD) [23]), the junction complexity and the already walked route. Based on this data, the system assesses the orientation and spatial confidence of the user. Then, the system predicts whether the user would select a rational option considering, among others, the maximum allowed walking distance [43]. If the resulting probability of committing a grave navigation error is high, the system supports the user with an instruction. By making own decisions, the user is expected to engage more with the environment and improve spatial knowledge acquisition. A user study comparing this system with a TBT navigation system (Organic Map) demonstrated that the FCN approach can give some decision-making freedom, significantly lowering the number of issued navigation instructions relative to the number of traversed junctions. No significant differences between both systems regarding spatial knowledge acquisition and workload (NASA TLX) were found. FCN was assessed as more stimulating and novel (UEQ) than TBT [45].

2.2 Augmented Reality Navigation

As the focus of this work lies on outdoor augmented reality (AR) navigation and given the differences between outdoor and indoor navigation regarding scale, landmarks, and navigation agents [20, 69], among others, we will not discuss AR-based indoor navigation (e.g., [18, 48]) . We will distinguish hand-held and head-mounted augmented reality navigation systems. Where applicable, we will report on spatial knowledge acquisition. The first prototypes using AR for pedestrian navigation date back to the 1990s [14, 63]. Given this era's technical and graphical limitations, we will consider only more recent research.

2.2.1 Handheld Augmented Reality Navigation. Handheld augmented reality systems require the user to hold a device, usually a smartphone or a tablet, to see and interact with the holograms. The AR navigation can be used for daily life, tourism [41], and disorientation [4] scenarios. Rehrl et al. [53] compared a handheld AR navigation system with voice-only guidance and a digital map. The results showed a higher workload and lower usability for AR participants. Dunser and colleagues [13] compared a handheld AR navigation system with a digital map (satellite view) and a combination of both. This combination was most preferred by participants and was also considered the fastest and leading to least errors. While using the AR-only interface, many users reported feeling lost. Dong and colleagues [11] compared two instances of the TBT navigation approach: 2D map vs. AR. The wayfinding performance between both groups did not differ. However, the eye-tracking data revealed differences between them, suggesting a lower cognitive workload (contrary to [53]). The AR interface led to sketch maps of lower quality. This stands somewhat in contrast to the work of [51] in which participants with an AR interface performed better regarding scene recognition, scene-sequencing and orientation judgment than those with a classical 2D map interface. Augmented reality can also be used for parts of the entire navigation process (e.g., destination recognition [50]).

2.2.2 Head-Mounted Augmented Reality Navigation. We will not discuss simulated AR navigation (e.g., [38]). Reitmayr and Schmalstieg [54] implemented an early version of augmented reality navigation with a head-mounted display. In the solo mode, the user was requested to follow a series of waypoints towards the destination. No formal user study was conducted. Cron and colleagues [8] implemented four different visualizations realizing an AR-based turn-by-turn approach. This preliminary work focused on visualization and implementation. McKendrick and colleagues [47] compared a head-mounted AR-based TBT navigation system with a classical smartphone-based approach and concluded that AR lowers the mental load while navigating. Singh and colleagues [61] introduced the concept of virtual global landmarks (VGL). These VGLs, representing landmarks like opera, become visible if the real counterpart (opera) is not visible anymore. In this case, a virtual icon of the landmark is projected into the user's field-of-view at a distance of one meter to convey the right direction towards the landmark. The within-subject user study with 5 participants showed that the VGL approach compared to directional arrows (also AR-based) has the potential to foster spatial knowledge acquisition. In our study, we will not highlight landmarks like VGL, but we make the destination always visible to the user. We convey the real location of the destination and not only the direction toward it.

There exist different visualization methods for AR-based navigation. Such methods usually highlight the route with arrows, overlaid paths, or checkpoint icons [8, 36]. However, they assume a pre-defined route that is incompatible with the beeline approach we are scrutinizing. Furthermore, they use the user position as a reference, whereas our visualization is permanently part of the environment, independent of the user position. In summary, our BeeAR system does not impose a predefined route to the user and displays the AR content embedded in the environment. To the best of our knowledge, head-mounted augmented reality has not yet been combined with beeline navigation to scrutinize spatial knowledge acquisition. Our paper aims to fill this gap.

3 EXPERIMENTAL DESIGN

The 16 participants of the BeeAR condition were acquired through emails sent to university employees in Vienna, Austria. They were not paid but offered participation in a lottery (400 EUR). The participants of the other two conditions were acquired with the same approach and, additionally, through snowball sampling (asking friends and acquaintances) [45]. In the following the navigation conditions, routes, and the experimental procedure are delineated.

3.1 Navigation Conditions

In this subsection, the details of all navigation systems are presented together with the required hardware and software.

3.1.1 Beeline Augmented Reality Navigation. In the *Beeline Augmented Reality* (BeeAR) condition, we used a Microsoft HoloLens 2 to display the destination's geographic location as a magenta cuboid (width: 10 m; length: 10 m, height: 150 m). This is the only information provided by the system. Before the experiment started, the beeline distance to the destination was communicated to the participant. The user should find her own way to the destination and make all decisions along the route, which stands in contrast to FCN (partial support regarding instructions) and TBT (full support). The closer the user gets to the destination, the bigger the magenta cuboid appears (see Figure 1). The user was requested to notify the experimenter when standing in front of the magenta cuboid. The HoloLens itself cannot display geographic coordinates, but we used a Helmert transformation to harmonize the HoloLens' coordinate system with a real-world reference system [15]. At the starting point, an accuracy of 5-10 cm is achieved, whereas an accuracy of approx. 5 m is achieved at the destination. In contrast to the FCN navigation approach, the destination is constantly visible to the user, therefore no user's orientation estimation is needed as in FCN. By adding this feature, we hypothesize to support spatial knowledge acquisition by giving participants an anchor point for orientation. Furthermore, the route can be selected freely, whereas FCN supports the user occasionally with instructions, and TBT imposes a predefined route on the user. Augmented reality was chosen as technology to liberate the user from the diffculty of matching provided spatial information with the physical environment, as the information is directly embedded in the latter. We deliberately selected a head-mounted display over a smartphone-based AR system to make the destination permanently visible to the user and to provide a hands-free and head-up experience.

3.1.2 Comparison Navigation Systems. This subsection briefly describes the Turn-by-Turn (TBT) and Free Choice Navigation (FCN) approaches [45]. In both conditions (TBT and FCN), the turn instructions were issued via a single Bluetooth earbud. The BeeAR did not comprise any type of instructions.

As a representative of the TBT navigation approach, we have selected the Android application *Organic Maps*. It provides a classical user interface with a map and a position indicator. While in navigation mode, the user receives instructions at turning points along a predefined path visible on the map. Besides displaying the route, the instruction is also conveyed in audio format. The application *Organic Maps* was running on a OnePlus 5T smartphone. A Global Navigation Satellite System (GNSS) receiver manufactured by PPM (model 10xx-38) was attached to the smartphone to increase the positional accuracy of the user location. The user was required to follow the highlighted route using the map and the provided audio instructions from the application. No further instructions or information were given along the route. Google Maps was deliberately not selected to assure comparability with the Free Choice Navigation approach based on OpenStreetMap (OSM) data. As the data source would have been different, the routing could have changed too. Therefore, we considered only navigation applications based on OSM.

In the FCN condition, before the navigation task started, the participant was provided two pieces of information: first, the direction to the destination (an arrow marked on the ground), and second, the beeline distance (transmitted orally, like in the BeeAR condition). The experimenter instructed the participant to find the unknown destination and underlined that the destination could not be missed, as the system informs the user upon arrival [45]. It was also explained that a junction and not a point of interest is the destination. Participants were not provided with turning instructions at the first two junctions, as their orientation should still be reasonable at this stage. At the following junctions, the system decided whether a turn instruction should be issued to help the participant (see Section 2.1.2 for details). If no instruction was issued, the participants had to decide which branch to take. The underlying mechanics of FCN were realized with a custom Kotlin application operated by the experimenter walking behind the participant.

3.2 Routes

To make the results comparable to the previous study [45], a subset of those routes was selected for the current study scrutinizing BeeAR. Route 1 (612 m) and Route 2 (738 m) (see Figure 2) were selected for the study, as for these routes the previous study yielded the least data loss. All participants were unfamiliar with the experiment area.

3.3 Procedure

The experiment consisted of two parts (online and in-situ). In the online part participants gave their informed consent, filled in a demographics questionnaire and reported if they are familiar with the experiment area.

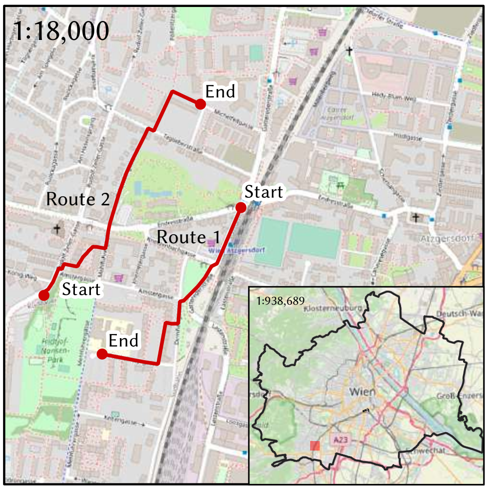

Fig. 2. Routes 1 and 2 were navigated by participants of all three navigation conditions. The experiment area is located on the outskirts of Vienna, Austria (see inset map). Background map OpenStreetMap.

In the in-situ part, participants were assigned to navigate on one of the two tested routes. The trial started after the informed consent was signed, the condition was explained and no questions were left. After the arrival at the destination, the participant had to fill out three questionnaires regarding workload (NASA TLX [22]), usability (System Usability Scale [2]), and user experience (User Experience Questionnaire [35]). Next, participants had to conduct five tasks assessing their acquired spatial knowledge: (1) Pointing to the start point; (2) Estimation of the walked distance (meters); (3) Abstract route drawing - drawing the sequence of turns and crossed junctions (i.e., non-turns); (4) Retracing the walked route on a map (called also route drawing task); (5) Draw recalled points of interest (POI) on the same map. The map contained the street network, the starting, and end points. Concerning the third task, the experimenter stressed that metric and absolute information are irrelevant in the drawing. Only the number and the sequence of turns were relevant. Before the fifth task, the experimenter provided categories of potential POIs (e.g., shop, restaurant, color of a building).

4 RESEARCH QUESTIONS AND HYPOTHESES

This subsection presents the research questions and justifications for our hypotheses.

- **RQ1:** Does the BeeAR approach lead to better spatial knowledge acquisition than FCN and TBT?
- **RQ2:** Does the BeeAR approach lead to longer routes (relative to shortest path) than FCN and TBT?

Regarding **RQ1**, we expected that BeeAR will improve spatial knowledge acquisition in comparison to FCN, because the destination is always visible and can serve an as anchor point [7]. Compared to TBT, we believe that BeeAR participants will remember more details of the environment (POIs) as they need to actively make decisions, whereas TBT users follow a predefined path. Regarding **RQ2**, we expect comparable relative route lengths (normalized by shortest path length) across navigation conditions as every navigation condition provides assistance, although of a different kind.

Table 1. Inferential statistics for the navigation conditions. Pairwise Wilcoxon-Mann-Whitney tests were performed if the Kruskal-Wallis (KW) test yielded p < 0.05. FCN - Free Choice Navigation, TBT - Turn-by-Turn, BeeAR - Beeline Augmented Reality. Significant results (Holm correction) are bold-faced. The numbers are rounded to three decimal digits.

Dimension	χ^2	p-value KW	FCN != BeeAR	FCN != TBT	BeeAR != TBT
Relative Walking Distance	20.679	**<0.001**	0.038	**<0.001**	0.004
Pointing Error (JRD)	0.953	0.621	-	-	-
Distance Estimation Error	5.922	0.052	-	-	-
Abstract Route Drawing - # Turns	0.420	0.811	-	-	-
Abstract Route Drawing - Lev. Dist.	0.443	0.801	-	-	-
Route Drawing on Map	17.379	**<0.001**	**<0.001**	0.002	0.551
# Point of Interests	10.378	0.006	**<0.001**	0.246	0.110
Point of Interests - 2D regression	1.571	0.456	-	-	-
NASA TLX - Mental Demand	4.687	0.096	-	-	-
NASA TLX - Physical demand	9.635	0.008	0.113	0.09	0.003
NASA TLX - Temporal demand	3.179	0.204	-	-	-
NASA TLX - Effort	6.068	0.048	0.065	0.69	0.019
NASA TLX - Performance	2.439	0.295	-	-	-
NASA TLX - Frustration	2.657	0.265	-	-	-
NASA TLX - Sum	8.335	0.015	0.007	0.571	0.029
SUS	1.414	0.493	-	-	-
UEQ - Attractiveness	3.813	0.149	-	-	-
UEQ - Novelty	18.179	**<0.001**	0.985	**<0.001**	**<0.001**
UEQ - Stimulation	7.594	0.022	0.776	0.015	0.021
UEQ - Dependability	0.555	0.758	-	-	-

5 RESULTS

Due to the non-normality of the data (Shapiro-Wilk tests and Q-Q plots), the Kruskal-Wallis test was employed for the comparison of all three groups and the Wilcoxon-Mann-Whitney test for pairwise comparisons. Given that a route can have a substantial influence on study results [44], a series of Wilcoxon-Mann-Whitney tests comparing two routes with their corresponding environments was calculated (similar to [62]). As both routes are similar according to the *Route Selection Framework* [45, 46], we expect no differences. The independent variables tested include: *normalized walking distance, pointing error, distance estimation error, abstract route drawing – number of turns, abstract route drawing - Levenshtein distance, route drawing on map, number of drawn POIs, drawn POIs - 2D regression, NASA, SUS and UEQ*. None of these tests reached significance (Holm correction [25]). This result allowed us to compare the navigation conditions independently of the two routes/environments (similar to [62]), having 16 samples for each condition. Only successful participants (destination reached with less than 1.5 * shortest path length) were analyzed. Therefore, one participant was excluded from the FCN condition, resulting in 16 participants per navigation condition (N_{total} = 48). If a Kruskal-Wallis test yielded p < 0.05, pairwise Wilcoxon-Mann-Whitney tests were conducted (see Table 1 for a summary). In order to avoid inflation of α-errors, corrections to the p-value according to Holm [25] were applied (baseline $\alpha = 0.05$).

5.1 Relative Walking Distance

As Route 2 (738 m) is longer than route 1 (612 m), we compared the walked distances normalized by the shortest path length. There was a significant difference ($\chi^2 = 32.966$, $p < .001$) between the navigation conditions. FCN ($M = 1.177$,

$SD = .118$) users walked significantly ($Z = -4.349$, $p < .001$) longer routes than TBT users ($M = 1.018$, $SD = .037$). There was no significant difference ($Z = 2.888$, $p = .004$) between BeeAR users ($M = 1.082$, $SD = .092$) and TBT. There was also no significant difference ($Z = -2.074$, $p = .038$) between BeeAR and FCN.

5.2 Spatial Knowledge Acquisition

This subsection presents the results regarding spatial knowledge acquisition: pointing to start point, walked distance estimation, abstract route drawing, route drawing on a map, and drawing points of interest on a map (see Section 3.3 for detailed task descriptions).

5.2.1 Pointing to Start Point and Distance Estimation. There was no significant ($\chi^2 = .953$, $p = .621$) difference between FCN ($M = 25.125°$, $SD = 34.517°$), BeeAR ($M = 17.625°$, $SD = 30.7°$) and TBT ($M = 18.25°$, $SD = 15.442°$) regarding the pointing to start point task. There was also no significant ($\chi^2 = 5.922$, $p = .052$) difference in the distance estimation task. FCN users over- or underestimated the walked distance on average by 95.465 m ($SD = 79.872$ m), whereas BeeAR users by 168.324 m ($SD = 290.9$ m) and TBT users by 263.885 m ($SD = 321.278$ m).

5.2.2 Abstract Route Drawing. In the abstract route drawing task, two features were compared. First, the difference between the drawn turns with respect to the number of actual turns made along the route (absolute value). Second, the difference between the drawn turning sequence and the walked one measured with the Levenshtein distance. There was no significant difference found between the groups for both features (see Table 1).

5.2.3 Route Drawing on Map. The similarity between the drawn and walked routes was calculated based on the dynamic time warping metric (DTW) [66]. A DTW distance of 0 indicates a perfect match between two sequences. Five FCN participants could retrace their walked route perfectly on the map. The same applies to 14 TBT and 15 BeeAR participants. There was a significant difference between the groups ($\chi^2 = 17.379$, $p < .001$). BeeAR participants ($M = 45.36$, $SD = 181.439$) retraced their walked routes significantly more accurate ($Z = 3.45$, $p < .001$) than FCN users ($M = 541.933$, $SD = 677.562$). The differences between TBT ($M = 69.407$, $SD = 253.31$) and FCN ($Z = 3.094$, $p = 0.002$) and BeeAR ($Z = -0.596$, $p = .551$) were not significant (Holm correction).

5.2.4 Points of Interest on Map. The drawn points of interest (POI) were analyzed along two dimensions. First, the number of actually existing POIs that were drawn on the map was counted. The Kruskal-Wallis test for the number of drawn POIs did not reveal a significant difference between the groups ($\chi^2 = 10.378$, $p = .006$ - Holm correction), but a post hoc test showed a significant difference ($Z = 3.424$, $p < .001$) between BeeAR ($M = 8.875$, $SD = 2.553$) and FCN ($M = 5.25$, $SD = 2.176$). There was no significant difference between TBT ($M = 7.25$, $SD = 3.624$) and BeeAR ($Z = 1.598$, $p = .11$) and FCN ($Z = 1.161$, $p = 0.246$) regarding the number of drawn POIs.

Second, the configuration similarity between the drawn POIs and the actual locations of these POIs was assessed by applying bidimensional regression [65]. The R package *bidimregression*, which builds on Friedman's work [16], was used for this analysis. To calculate the R^2 coefficient, at least four pairs of coordinates are needed [49], therefore, only participants with more than three existing POIs are analyzed ($n = 43$, BeeAR = 16, FCN = 14, TBT = 13). Regarding the configuration similarity, there was no significant ($\chi^2 = 1.571$, $p = .456$) difference between BeeAR ($M = 0.9$, $SD = 0.156$), FCN ($M = 0.822$, $SD = 0.267$) and TBT ($M = 0.879$, $SD = 0.256$).

5.3 Workload and User Experience

This subsection presents the results regarding the subjective workload and user experience each navigation system excited.

5.3.1 SUS. There was no significant difference ($\chi^2 = 1.414$, $p = .493$) regarding the System Usability Scale (SUS) between BeeAR ($M = 82.031$, $SD = 9.047$), FCN ($M = 84.844$, $SD = 7.878$), TBT ($M = 80.156$, $SD = 12.957$). The FCN navigation system falls into the highest category "A+" in the Sauro–Lewis SUS curved grading scale [57], whereas BeeAR falls into the second-highest category "A" and TBT falls into the third-highest category "A-".

5.3.2 UEQ. Two out of six subdimensions of the UEQ questionnaire could not be compared across all three navigation systems. As FCN has no graphical user interface, two questions (21 and 23) contributing to the excluded subdimensions *perspicuity* and *efficiency* were not asked. These subdimensions were compared only between BeeAR and TBT. Neither for *efficiency* ($Z = .495$, $p = .621$) nor for *perspicuity* ($Z = -1.041$, $p = .332$) a significant difference was found. For the subdimensions *attractiveness* ($\chi^2 = 3.813$, $p = .149$), *dependability* ($\chi^2 = 555$, $p = .758$) and *stimulation* ($\chi^2 = 7.594$, $p = 0.022$ - Holm correction) no significant differences between the three navigation systems were found (see Table 1). The test for the subdimension *novelty* yielded a significant difference ($\chi^2 = 18.179$, $p < .001$) between the groups. TBT participants ($M = -0.516$, $SD = 1.321$) indicated the novelty of the system as lower than BeeAR ($M = 1.453$, $SD = 1.166$, $Z = 3.624$, $p < .001$) and FCN ($M = 1.484$, $SD = .964$, $Z = 3.72$, $p < .001$) participants. Between the latter two groups, there was no significant difference ($Z = .019$, $p = .985$) regarding *novelty*. BeeAR and FCN have very high hedonic quality (excellent stimulation and good novelty), whereas the TBT navigation system has a below average hedonic quality (below average stimulation and bad novelty). The pragmatic quality of BeeAR (excellent perspicuity, good efficiency and good dependability) is higher than in case of TBT (good perspicuity, above average efficiency and above average dependability).

5.3.3 NASA TLX. Although differences could be observed in all subdimensions and the overall sum (see Figure 3), none of the Kruskal-Wallis tests nor the post-hoc tests yielded significant results (see Table 1).

6 DISCUSSION

This section discusses the findings of this real-world user study and compares the outcomes with previous literature. The discussion highlights the advantages and disadvantages of the BeeAR approach compared to FCN and TBT.

First, we want to clarifiy the term *engagement with the environment*. By this we mean a higher level of attention paid the to environment. FCN and BeeAR have no second display to distract the user and should support this engagement. However, BeeAR users remebered more POIs and could retrace their routes better than FCN users. We believe, that this is the consequence of the permanently visible destination rather than the employed augmented reality (AR) technology. AR-based navigation on its own does not necessarily improve spatial knowledge acquisition [11]. However further studies, comparing BeeAR with AR-based TBT navigation [36] might help to shed light on this topic. Similar to our previous work [45], the proposed novel navigation approach (BeeAR) did not lead to statistically significant differences concerning spatial knowledge acquisition compared to TBT (**RQ1**).

Although BeeAR leaves all decisions to the user (partially true for FCN), the walked routes are not considerably longer compared to routes walked by TBT users following the shortest path (**RQ2**). This finding suggests that having the destination in line of sight might be sufficient for successful navigation. Given that TBT users see a digital map while navigating, it is not surprising that 14 out of 16 TBT participants could retrace their route perfectly on a map. Although

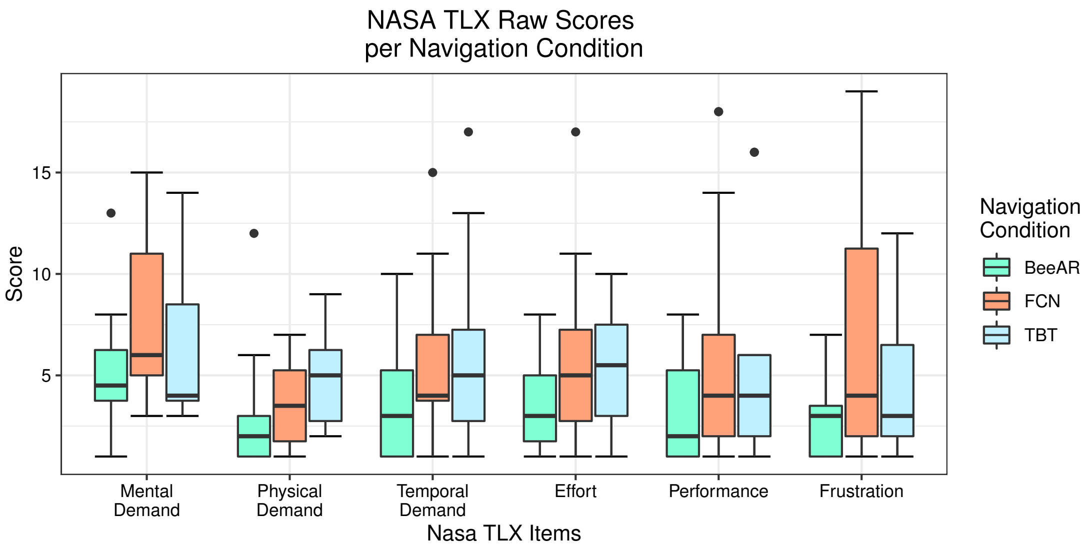

Fig. 3. Box plots of nasa TLX raw scores by navigation condition. None of the observed differences was statistically significant (see Table 1).

there was no map in the FCN and the BeeAR conditions, BeeAR users retraced their walked routes significantly better than FCN participants. Notably, all but one user in the BeeAR condition retraced the walked route perfectly, although no map was provided. This might be due to the destination always being visible in the BeeAR condition, serving as an anchor point to orient [7]. Another possible explanation is that BeeAR users had the comfort of looking around while knowing exactly where the destination is. In contrast, FCN users were required to orient themselves along the route. This extra effort might explain the slightly higher mental demand and frustration in the FCN condition. In this group, the interquartile ranges are also larger (see Figure 3). The TBT system not having a negative influence on the ability to retrace a route is in line with [31], although, in our experiment, the route drawing task on a map cannot be considered a pure route knowledge task as the route needed to be integrated into the environment. The comparable results of BeeAR and TBT are particularly interesting, as they suggest that a map is not necessarily needed to build up survey knowledge [64]. BeeAR participants draw significantly more points of interest (POI) on a map than FCN users. Maybe, the lower level of effort, mental demand, and physical demand experienced by BeeAR users could have contributed to this positive effect in recalling POIs. BeeAR participants were not confronted with the *"being lost"* feeling, whereas FCN users have potentially experienced it, as they were provided the direction to the destination only once at the beginning of the route. As a navigation approach that combines own decisions with confidence about the destination location, BeeAR could have led to increased engagement with the environment and, consequently, to a higher number of remembered details thereof. This conclusion stands somewhat in contrast to the work of [40] in which the redirection of the user's attention to the environment improves route and landmark knowledge. In our experiment, both systems required the user to engage with the environment. However, given the observed differences in the number of drawn POIs, this alone was insufficient to acquire more accurate spatial knowledge. There is a tendency for BeeAR users to draw more POIs than TBT participants despite not having access to a map. Although this difference is not statistically significant, BeeAR can be considered a valuable alternative to TBT for users interested in learning more about their environment, as they can entirely focus on their surroundings without looking at a screen.

Although the observed differences in physical demand were not statistically significant, we want to briefly discuss their potential origin. In contrast to TBT, BeeAR and FCN participants navigated hands-free. This circumstance might explain the reported lower physical demand, although our results are in line with [52]. The main difference between BeeAR and FCN users was that for the former the target was always visible. This may have caused fewer head rotation movements compared to FCN. Furthermore, the technology of the BeeAR approach may have caused participants' excitment and make them forget about the head-mounted display they were wearing.

Participants of all three navigation conditions achieved a high configuration similarity, expressing the similarity between the drawn POIs and their actual locations. Considering that two navigation conditions did not make use of maps and therefore can be comparable to a "direct experience" approach, this result contrasts the work of [29]. Different from our findings, in [29], participants with direct experience (following the experimenter) drew topologically more accurate sketch maps than participants with a mobile map-based TBT navigation. Although not significantly, BeeAR users estimated their walking distance worse than FCN but better than TBT, suggesting that own decisions along the route may contribute to a better sense of walking distance. Contrary to our results, in the work of Kuo and colleagues [34], participants using an AR-based beeline navigation approach paid little attention to the environment because being heavily focused on the arrow pointing towards the destination. This difference may have its origin in the different use of AR between the two systems. BeeAR is a head-mounted system displaying the exact location of the destination (while the user is looking in the direction of the destination) rather than constantly showing the direction to the destination (in form of an arrow) on a hand-held device.

The novelty (UEQ) of both BeeAR and FCN was rated higher than in the case of TBT, which is not a surprise as this type of navigation is part of daily life for many people. The same applies to stimulation (UEQ). This can result from the necessity of making own decisions and engaging with the environment. The pragmatic quality of BeeAR was higher than for TBT, indicating that BeeAR users felt safe, in control, and experienced the system as easy to learn. Regarding usability (SUS), no significant difference was found between the systems. However, it has to be noted that the used TBT application was not Google Maps. The usability of that navigation application is potentially higher than this of Organic Maps [26]. In [59], cyclists reported a higher workload in the beeline navigation condition (similar to a compass) than with a TBT navigation system. This is not in line with our experiment. Our BeeAR approach combines the beeline approach with the exact location of the destination. The second part may have led to a decreased overall workload compared to [59]. In the work of [26], Google Maps was compared with the PRA navigation approach in which users are also required to make own decisions, similar to the BeeAR approach. The PRA approach caused significantly higher mental demand than the usage of Google Maps. This stands in contrast to our results. The two routes did not yield differences regarding the compared metrics , which indicates the usefulness of the route selection framework [46].

In summary, it can be said that BeeAR performs comparable to TBT regarding spatial knowledge acquisition and workload, although no map is provided in this condition. Regarding the hedonic and pragmatic quality (UEQ), BeeAR outperfroms TBT. BeeAR users remembered more POIs and retraced their walking route better than FCN participants. In addition, the presented navigation approach opens new research directions, especially when wayfinders become familiar with the employed AR technology.

7 CONCLUSION, LIMITATIONS, AND FUTURE WORK

We presented a novel navigation system combining augmented reality and beeline navigation (BeeAR). In contrast to previous works (e.g. [39]), our system displays the proper destination location and not only the direction toward it. We compared BeeAR with findings from a previous study comparing Free Choice Navigation (FCN) and Turn-by-Turn (TBT) navigation conducted along the same routes on the outskirts of Vienna, Austria. Fifteen out of 16 BeeAR users retraced their walked routes perfectly, although no map was provided. Although statistically not significant, they remembered more environmental details along the route than TBT users. This could be because BeeAR combines own decisions along the route with confidence in reaching the destination, which implies a high level of engagement with the environment.

Although the study results are encouraging, several limitations apply to our work. The destination is always displayed but only visible if the user is looking toward it. If the user faces another direction, an off-screen indication [21] could have helped the user to improve orientation. As BeeAR is a hands-free and visual navigation approach, it is inadequate for users with visual impairment. Non-visual alternatives (e.g., vibrotactile and voice-based) have been discussed in Section 2. The graphical user interface of BeeAR is currently displaying only the destination as a magenta cuboid. Further information or feedback regarding the performance could help the user to build more trust. We deliberately decided to make the destination always visible while facing it and not to hide it behind urban infrastructure to maintain orientation. However, this circumstance is not favorable to augmented reality's known depth perception problem (e.g., [1]). Adding visual cues can mitigate this problem, e.g., occlusion by buildings, vegetation, and cars. We are aware that our BeeAR approach may be less effective in environments with dead ends [58].

Regarding future work, there are several strands to follow. Enriching the graphical user interface with further information (e.g., [42]) may help the user to orient better (e.g., highlighting points of interest). The destination can be made visible on demand. This would probably increase the mental demand slightly, but also increase the involvement with the environment. One participant proposed that the distance to the destination can be reflected in its color (e.g., far away - blue, very close - red). In order to address this new research questions, further user studies are planned. Another future research direction is the virtual character of landmarks and its influence on spatial knowledge acquisition. In our study, it was only the destination, which was not expected to be memorized, but maybe placing further virtual landmarks in the environment would increase the retention of spatial relationships. Furthermore, the effect of highlighting global and local landmarks on spatial knowledge acquisition can be investigated with our AR approach.

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CHAPTER 9

Discussion

This section will discuss the results of the presented articles, mainly those not already addressed in the articles. Several already discussed issues will be deepened in this section. First, the results concerning route selection will be discussed. Second, the influence of making own decisions along the route on spatial knowledge acquisition will be thematized.

As the route selection process receives little attention in the literature (see Chapter 2), a route selection framework was proposed. It aims for systematic and reproducible route selection for wayfinding studies and helps to make the considered route features explicit (**RQ2**). The framework's flexibility is shown by the readily substitution of features describing the routes according to research needs and data availability. The proposed framework is meant as an assistance and recommendation tool. The final suitability of the route for a given experiment can only be assessed with expert knowledge and in-situ checks, as not every detail of the environment is captured in available data and may, therefore, be unperceivable during the route selection process. The viability of this approach was shown through simulation and real-world studies.

Another aspect contributing to the flexibility of the framework is the specification of the *target route*. It can be an average-based route reflecting the whole route population regarding all relevant route features. The target route can also be any real or hypothetical route selected by the researcher. This enables finding similar routes in different geographic areas and can be seen as a first step to facilitate study replications in different environments (**RQ3**). A simulation study (see Chapter 4) showed that the framework is valuable for replication studies using navigation approaches sticking to a predefined route (e.g., TBT) but needs further improvement for navigation approaches giving the user more freedom (e.g., FCN and BeeAR). The route selection framework can be used for any transportation mode: walking, cycling, driving, etc. It does not select routes completely autonomously since the researcher is responsible for several input variables (e.g., the length of the route and the number of decision points).

The first application of this framework in a real-world wayfinding study showed a further important input of the researcher: in-situ checks. According to the data, several routes were suitable regarding points of interest (POI). However, in-situ screenings revealed that several POIs are barely visible along the route, as they were covered by vegetation, for example. Based on this observation, a checklist accompanying the route selection process originated (see Chapter 7). This checklist is not appropriate for every wayfinding experiment, as the underlying research questions impact potentially available routes and features describing them. The current version of the route selection framework uses the weighted Euclidean distance to express the similarity between routes. Although the framework's usefulness for route selection was shown in simulation and real-world studies, the meaning of the selected distance metric concerning wayfinding studies is still a subject of future research, i.e., it is unclear which difference in terms of weighted Euclidean distance needs to be reached to yield different study results.

The research regarding the potential influence of routes on the results of wayfinding studies and the proposition of the route selection framework originated from the lacking knowledge about the first aspect. As there was no systematic knowledge about this potential influence, it could have been that the selected routes for the wayfinding studies induced an unknown bias. The selected routes may have been advantageous for the tested navigation system, but at the same time, there may have been a route on which the navigation system does not perform well. Both cases are problematic if unnoticed, as results might not be generalizable. I do not claim that all previously conducted wayfinding studies are of no value, but the results should be interpreted with caution, as the selected route, by chance, might have disadvantaged/favored the expected results. This work is supposed to spark a discussion about whether route selection in wayfinding studies is a problem, and how to approach this potential difficulty. This thesis contributed to the discussion by running an agent-based simulation study in the city center of Vienna, Austria. As calculating all possible routes (varying length and number of decision points) is an NP-complete problem, the population was limited to all shortest paths having 12 decision points and a length between 550 m and 1000 m. Considering not only the shortest paths between two points is a reasonable option for further research (e.g., Zhu and Levinson, 2015). The simulation showed that depending on the route, one or the other navigation system is superior, although, on average, one system is better (**RQ1**).

This result indicates that route selection is a crucial step in experimental design and has the potential to influence, if not steer, the outcomes of a wayfinding study. Therefore, a discussion in the community conducting navigation experiments is needed to determine how to deal with this potential bias. An additional finding of this study is that the turnover of the results is even more likely if the sample size (the number of agents) decreases (**RQ4**). The results are valid for the city center of Vienna and likely generalizable for cities with a similar network structure (Strano et al., 2013; Thompson et al., 2020). The verification in cities with different network types (similar to Savino et al., 2022) and a real-world study are the next steps in order to consolidate the understanding of the route selection problem.

A potential remedy to the turn-over problem of the results was proposed (see Chapter 5). This route selection approach is based on an agent-based simulation with all potential routes and different sample sizes. The idea is to select routes along two criteria. First, routes with consistent results across sample sizes are selected. Second, routes in line with the global trend are found (e.g., average across all routes). This two filtering steps result in a list of potentially suitable experiment routes. They can be further ranked with the above-mentioned route selection framework, as the list possibly contains hundreds or more routes. The requirement for this approach is to run an agent-based simulation. In consequence, this route recommendation procedure is only as good as the underlying simulation. Further solutions could deal without running an agent-based simulation study, e.g., predicting the success metric based on route features. A database with data from all over the world regarding the same navigation system (e.g., Google Maps) could be established to provide training data. This step, however, would require further harmonization steps as instructions for participants are likely to vary across studies. Given the substantial influence routes can have on study results, a discussion about how to deal with this problem should take place. The proposed remedy is only one possibility for coping with this problem. Different approaches may be more efficient and easier to follow. These discussions should also address the generalizability of study results, e.g., this aspect becomes especially important if the selected routes are very short.

The second part of this section discusses the findings of the real-world study that scrutinized the influence of own decisions on spatial knowledge acquisition (**RQ5**). The inspiration for this study was the ongoing discussion about whether navigation assistance systems negatively affect our spatial cognition (e.g., Ishikawa, 2019; Ruginski et al., 2019). The work of Lu et al. (2021) suggests that redirecting the user's attention to the environment and involving the user in the path planning procedure supports spatial knowledge acquisition and self-orientation. Therefore, it is reasonable to research navigation systems that let the user engage with the environment and leave, at least partially, navigation decisions to the user. Two such navigation systems were proposed and tested in a real-world urban environment: *Free Choice Navigation* (FCN, see Chapter 7) and *Beeline Augmented Reality* navigation (BeeAR, see Chapter 8).

The viability of the FCN concept was first tested by means of an agent-based simulation study. More than 90% of the agents reached their destination in the three test environments. These encouraging results led to a real-world prototype of this system. First, the results comparing FCN and TBT are discussed and later, the observed differences between BeeAR and FCN and TBT, respectively, as this reflects the development chronology. Twenty-three FCN participants (out of 26) reached their destination successfully. This share is in line with the simulation study conducted previously. One participant misunderstood a turn instruction. Instead of having pure turn instructions, one might consider incorporating landmark information into the instructions (Tom and Denis, 2003). Simple turn instructions were used to maintain comparability with the tested TBT system. Two participants did not receive an instruction at a crucial junction (in retrospect). A future feature that needs to be considered is the junction's importance for a given route (e.g., Teimouri and Richter, 2022).

The FCN system issued less navigation instructions than TBT, relative to the number of traversed junctions. Compared to the TBT approach, FCN users would receive one instruction less every six junctions they traverse. For the experiment, it meant that FCN users had to make own decisions at 60% of the junctions, whereas TBT users at 44%. Making own decisions requires the examination of the environment. Although the FCN approach incorporates independent navigation with own decisions, FCN users did not show improved spatial knowledge acquisition compared to TBT (in line with Chrastil and Warren (2013), in contrast to Bakdash et al., 2008). This stands somewhat in contrast to the work of Lu et al. (2021) in which the redirection of the user's attention to the environment can lead to increased landmark and route knowledge. Persuading the user to engage with the environment is, on its own, not enough to foster spatial knowledge acquisition (in contrast to Parush et al., 2007). Although no significant differences were observed, tendencies will be discussed in the following. Regarding the pointing task, the results are in line with Huang et al. (2022) (no significant difference between both systems). This result contrasts with the work of Clemenson et al. (2021) in which participants who were new to the experimental area were more accurately pointing to other locations after navigating with a system that leaves decisions to the user. FCN users estimated the walking distance by 115 m more accurately than TBT users, suggesting that FCN supports proprioception. On average, TBT participants retraced the walking route more accurately and remembered more points of interest than FCN users. This tendency does not surprise, as TBT users were supported with a mobile map indicating landmarks. However, the high configurational similarity of FCN participants is notable, as these users had no map showing the entire area including landmarks. This result differs from findings of Münzer et al. (2006) in which participants with a (paper) map acquired better survey knowledge than participants not supported with a map. In the presented study, FCN users could acquire accurate survey knowledge without being provided with a map. The reported *mental demand* (NASA TLX) of FCN participants was, on average, higher than that of TBT users. The same applies to *frustration*. This may stem from the need to stay oriented and not knowing exactly where the destination is located. The higher mental demand could also be caused by making own decisions, which would be in line with Huang et al. (2022).

One of the limitations of the FCN approach is the estimated user orientation. In order to overcome this potential drawback, a second navigation system called BeeAR was proposed. There, the destination is permanently visible and consequently facilitates orientation. Furthermore, the displayed digital landmark may serve as an anchor point for orientation (Couclelis et al., 1987). BeeAR participants retraced their walked routes better than FCN participants. This is likely to be caused by the permanently visible destination, as BeeAR users did not need to orient themselves with respect to the destination. The discussed differences regarding the NASA TLX questionnaire were statistically insignificant, but the observed tendencies may explain other results. The destination information was readily available to BeeAR users, whereas FCN participants had to reorient themselves frequently, also causing slightly increased levels of *mental demand* and *frustration*. BeeAR users rated their *performance*, on average, higher than FCN and TBT users. As the destination was given in the BeeAR approach, participants potentially could focus on the environment as other potentially distracting objects were missing. Interestingly, 15 out of 16 BeeAR users retraced their walked route perfectly, given that no map was present in this navigation condition. The same applies to 5 FCN and 14 TBT users. In line with Kelly et al. (2022), the TBT system did not negatively impact the ability to retrace the walked route. However, the employed route drawing task cannot be considered a pure route knowledge task because the route needed to be integrated into the environment. This result suggests that the acquisition of survey knowledge (as the route needed to be integrated into the street network) can be supported by other means than maps (Thorndyke and Hayes-Roth, 1982). Another interesting finding of this study is that BeeAR users drew more points of interest than FCN users, although none of them had a map. The certainty of BeeAR participants of knowing where to go could explain this result.

The time FCN users spent on reorientation (causing increased *mental demand*), BeeAR users could observe the environment to decide which branch to take next. These differences between BeeAR and FCN suggest that redirecting the user's attention to the environment is not enough to foster spatial knowledge acquisition (Lu et al., 2021). BeeAR users recalled, on average, more POIs than TBT users. The combination of own decisions, i.e., keeping the user active (Parush et al., 2007; Lu et al., 2021), and spatial confidence (seeing the destination permanently) may have led to this positive effect. The configuration similarity between recalled POIs and their true locations was high in all three navigation conditions. Why users of two navigation systems without any map performed as good as users having a map will be the subject of future research, as currently, survey knowledge support is mainly attributed to interactions with overviews (e.g., maps) of the experiment area (e.g., Thorndyke and Hayes-Roth, 1982; Golledge et al., 1995; Münzer et al., 2006; Löwen et al., 2019). Given these positive results in the BeeAR group, a further advantage compared to hand-held devices can be derived. As the user does not need to map information presented on a screen to the environment, the user can focus entirely on the environment and, consequently, acquire more spatial knowledge (in contrast to Kuo et al., 2020).

The results of the conducted real-world user study somewhat contrast with certain empirical evidence suggesting an adverse effect of TBT-based navigation systems on spatial knowledge acquisition (see Section 1.2.2). In the work of Hejtmánek et al. (2018), increased map use led to increased pointing errors and worse performance during location placement and naming on a blank map. BeeAR and FCN participants were not supported with a map, whereas TBT users had constant access to a mobile map. Nevertheless, TBT participants did not perform significantly worse in any tasks approximating spatial knowledge acquisition. The *direct experience* navigation condition in Ishikawa et al. (2008) is comparable to BeeAR and FCN because the user is encouraged to engage with the environment. Results show that participants using a GPS-based TBT navigation system traveled longer distances, committed larger pointing errors, and drew sketch maps of lower topological quality compared to *direct experience* participants. In our study, TBT users had the shortest walking distances (on average), performed comparably to BeeAR and FCN in the pointing to start point task, and achieved a high configuration similarity between the drawn POIs and their true locations. The differences reported in Ishikawa et al. (2008) may also originate from an early stage of commercial pedestrian navigation systems. Krüger et al. (2004) compared two modalities for turn-by-turn navigation (PDA vs. head-mounted clip-on display). They conclude that TBT favors landmark knowledge but not survey knowledge. The second part contrasts with the presented results, as TBT participants could retrace walking routes very well and achieved a high configuration similarity of drawn POIs. Fenech et al. (2010) compared audio-based turn-by-turn navigation with self-guided navigation regarding scene recognition. Participants guided by the TBT system performed worse in the scene recognition task, suggesting that it causes inattentional blindness. In the presented study, TBT participants remembered a comparable number of POIs. This study focused on short-term implications of own decisions and engagement with the environment for spatial knowledge acquisition. Therefore, studies considering the lifetime experience with TBT-based navigation systems are not further discussed (e.g., Ishikawa, 2019; Dahmani and Bohbot, 2020). Nevertheless, on a short-term scale (navigating one route), no negative effect of TBT navigation on spatial knowledge acquisition was observed during this study (in line with Sönmez and Önder (2019) and Kelly et al., 2022). Even if TBT has no adverse effect on spatial cognition, research on navigation systems supporting spatial knowledge is still relevant as users expressed a strong interest in learning more about their environment, even for the price of walking longer routes (**RQ6**, see Chapter 7).

Above, this section provides several potential explanations about why different study results regarding spatial knowledge acquisition were observed. The contrast between this work and previous research could also originate from using different routes and environments since route selection can substantially impact study results (see Chapter 5). Potential differences between routes across experiments are landmarks, route length, turning sequence, and environmental type, among others. These differences can lead to different results, even if the experimental setup is similar. One possibility to make the results more comparable is to rerun an experiment either on the same route as the comparing experiment or on a similar route identified by the presented route selection framework. Finally, we shall not forget about the human factor here, as cultural and personal differences may influence study results too (e.g., Ishikawa and Montello, 2006; Montello and Xiao, 2011).

CHAPTER 10

Conclusions, Limitations, and Future Work

10.1 Conclusions

This thesis presented a framework for systematic and reproducible route selection for wayfinding studies (**RQ2**). It aims to find *average* routes reflecting the given experiment area, and by this, increasing the generalizability of the findings. Routes are described with features (e.g., mean segment length, the number of right turns) that can be flexibly selected by the researcher according to her needs and data availability. The framework's practical value was shown in a real-world user study by recommending routes in the experiment area. The final decision always needs to be made by the researcher, as certain aspects might not have been captured in the route features (e.g., missing data). The same framework allows for finding similar routes in different geographic areas, and in consequence, facilitates the replication of wayfinding studies (**RQ3**). Furthermore, it helps to make route selection choices and considerations explicit. In conclusion, the framework can be applied in any scenario involving route selection (e.g., wayfinding studies and urban computing).

The potential influence of routes on study results was investigated by means of an agent-based simulation study (**RQ1**). The results suggest that routes can greatly impact study results, and depending on the selected route, the study outcome may be inverted. It was the first systematic work in this area, directing the community's attention to the potential problem of ad-hoc decisions for route selection in wayfinding experiments. The results also indicated an aggravation of this problem with decreasing sample size (**RQ4**). Given this problem, an approach to select suitable routes incorporating the route selection framework was proposed.

Two novel navigation approaches (FCN and BeeAR), increasing decision freedom and engagement with the environment, were proposed to improve spatial knowledge acquisition (**RQ5**). They were tested in a real-world urban environment on the outskirts of Vienna. The widespread TBT approach acted as baseline condition. FCN and BeeAR participants did not perform significantly differently from TBT users in tasks approximating spatial knowledge acquisition. However, BeeAR users retraced the walking route better than FCN users, although both navigation conditions did not include a map. BeeAR users also recalled more points of interest compared to FCN participants. These differences indicate that making own decisions along the route is, on its own, insufficient grounds for improving spatial knowledge acquisition. Interestingly, participants in all three navigation conditions achieved a high configuration similarity between drawn points of interest and their true locations (bidimensional regression). This result suggests that a map is not necessarily needed to build topologically accurate survey knowledge. A survey showed that learning about the environment incentivizes walking longer routes (**RQ6**). This reason was preferred over being in control of the walked route, indicating that everyday users appreciate research on navigation assistance systems supporting spatial knowledge acquisition. The results of the conducted user study did not provide empirical evidence for TBT navigation being harmful to spatial knowledge acquisition in pedestrian wayfinding.

10.2 Limitations and Future Work

This subsection will discuss limitations and strands of future work together, as future work partially results from the limitations of the current work. As in every research, several research questions have been answered, but on the other hand, new research questions have arisen, pointing to different research directions. First, further research challenges considering the route selection framework together with route importance in wayfinding experiments are discussed, and second, new research questions are highlighted regarding decision freedom along the route (mainly Free Choice Navigation and Beeline Augmented Reality navigation) and spatial knowledge acquisition.

The route selection framework is very flexible, as every available data describing routes can be used to find representative average-based routes. Until now, mostly geometric features were used, e.g., segment length and the average number of branches at junctions. Adding points of interest and land cover data was a first step to incorporate semantic information, and by this, increase the similarity between routes. In order to make this distance measure more intuitive to humans, further semantic and visual measures could be added to find representative/similar routes. Several measures such as perceived scene complexity (Guan et al., 2022), street-view greenery (X. Li et al., 2015), building age (Sun et al., 2021), and visual enclosure (Yin and Wang, 2016) can be extracted from street view imagery (see He and G. Li (2021) for an overview) and integrated into the framework. Furthermore, data considering architectural style and safety can enrich the route selection framework and extend it beyond the geometrical dimension. The temporal dimension can be integrated by using the perceived travel time (Parthasarathi et al., 2013). Additional features describing the route can target health (pollution), crime, and cognitive effort (see Siriaraya et al. (2020) for an overview). Most of the considered and mentioned features are symmetric. The route from A to B would get the same score as the route from B to A. One asymmetrical feature is the terrain slope, making one of the routes potentially more physically demanding. Another argument for having asymmetric scores is the preference of wayfinders to long legs at the beginning of a route (Brunyé et al., 2015), or significant route differences if start and end points are swapped (Bongiorno et al., 2021). The route selection framework depends on data availability. Some features describing routes would be available worldwide, whereas other data, such as digital elevation models, are either available in different resolutions or only on a regional/local scale. Even potentially near global-coverage data needs to be computed first (e.g., mean segment length based on OpenStreetMap). This step might represent an obstacle to using the framework, particularly for users without a programming background. Therefore, it would be of great benefit to have a database with several pre-computed features, ideally for the whole world (Fogliaroni et al., 2018). In an ideal world, different stakeholders would contribute their data to this database. This would lower the entry barrier to start using the route selection framework across different disciplines.

As shown in Chapter 4, the route selection framework can be used to increase the comparability of wayfinding studies. By making the route describing features robust and covering human perception, wayfinding results may be compared without using the same navigation system over and over again. This might be of particular interest, considering that in many wayfinding studies the turn-by-turn navigation approach acts as a baseline. With an appropriate distance metric, one could estimate the performance of TBT in a given area without actually conducting this condition, as much data regarding TBT navigation has been collected. As of now, the weighted Euclidean distance is used in the route selection framework, allowing for prioritizing one feature over the other. Besides the weighting, the selected distance measure impacts the outcome of the framework. The cosine similarity measure was excluded (see Section 2), however, different distance metrics, such as the Manhattan or the Minkowski distance, should be scrutinized for suitability. The interpretability of the score every route obtains is still under investigation and currently presents a limitation of the framework. Therefore, real-world user studies need to be conducted to shed light on the interpretation of this score. In the current implementation, the user of the route selection framework needs to specify the route length in terms of junctions. This design decision was made because calculating all possible routes between n and m junctions was time-wise not practical, even in middle-sized cities. This is known as the subgraph isomorphism problem that is NP-complete. However, if certain constraints apply to the graph and the street network is modeled as a planar (Buhl et al., 2006) and simple (without loops and multiedges) graph, the problem can be solved in linear time using graph partitioning and dynamic programming (Eppstein, 2002). For several areas, the assumption of planarity is met, whereas in areas with bridges, overpasses, and tunnels this approach is problematic and does not reflect reality. Therefore, a more practical solution needs to be developed. The solution could also be an approximation of all possible routes with a specific number of decision points instead of an exhaustive list thereof.

A route to be followed never exists on its own. It is always embedded in a street network. If the planned path is not followed (due to navigation errors, for example), the route's surroundings are also experienced. Several navigation approaches favor exploring the environment surrounding the shortest path (e.g., FCN and BeeAR). Therefore, it is also essential to describe this neighborhood reliably to select an appropriate route for a wayfinding experiment. However, how to define this *neighborhood* exactly is still unclear, and it depends on the navigation system at hand (Canestrini, 2023). The importance of the route's neighborhood becomes clearer with the following example. The user follows the shortest path but misinterprets one turning instruction and ends up in a dead-end. This situation may increase the uncertainty of the user and make further navigation errors more likely. In consequence, the surrounding area of the route should be considered to describe a route, as the route itself may not be complex, but the surroundings might be. This aspect also needs to be added to the route selection framework as a further improvement.

It was shown that route selection has the potential to invert study results and is all the more critical with decreasing sample size (see Section 5). As this simulation study was conducted in the city center of Vienna, further studies in cities with a different street network layout (Thompson et al., 2020) are needed to confirm the results. Depending on the navigation approach (e.g., TBT, FCN and BeeAR), different features of the street network will impact the navigation experience. Savino and colleagues (Savino et al., 2022), for example, showed that a grid-like structure and few dead-ends, among others, are network properties favorable to beeline navigation. The most important feature of any navigation system is to guide users successfully to their destination. Nevertheless, the work on route importance may be extended by using success metrics other than arrival rate. Depending on the experimental design, detour length, spatial knowledge acquisition, or the number of erroneous decisions might be of interest. Therefore, for studies measuring not only the arrival rate, further research is needed on how other performance metrics are affected by route selection. As a simulation is always a simplification of the real world, a wayfinding experiment in real-world settings is needed. A possible experimental design could look as follows: (1) take all potential routes and divide them into categories, e.g., according to their score (route selection framework) or the arrival rate from a previous simulation study; (2) for each of these groups, select one route that best represents the group; (3) compare different navigation systems regarding various performance metrics on these routes; (4) verify if different routes lead to differences in performance metrics.

In its current form, the Free Choice Navigation system has certain limitations. Some improvements can be implemented immediately, whereas others need further research. The point in time at which a "go-back" instruction is issued can be optimized. It can be communicated shortly after the junction at which, probably, a non-optimal decision was made. This change would save evitable walking distance and improve the arrival rate in the FCN navigation approach. The Free Choice Navigation mechanism depends on a series of parameters, such as the maximum allowed path length and a penalty factor for already visited junctions, that directly impact the support given by the system. A parametrization resulting from the previous simulation study was used in the in-situ study. Depending on the street network, this parametrization may vary. Therefore, a real-time adaptation given the current area is a possible extension of the presented work, e.g., going from one city district to another that differs considerably regarding street layout. It is unlikely to have one parameter set that works well on a global scale because the street network characteristics directly influence the working mechanics of FCN. Whether the system assists the user depends as well on the complexity of the current junction. There are different approaches to assessing a junction's complexity. In the in-situ study, the complexity of a junction depended on the number of branches. The more branches, the more complex the junction was (O'Neill, 1991). Further complexity measures must be tested, as they potentially improve the navigation system. A more accurate junction complexity measure allows for assisting the user more accurately and helps to provide assistance when actually needed. Therefore, further studies with other modeling approaches concerning junction complexity (Giannopoulos et al., 2014; Guan et al., 2022) are needed.

Before assessing a junction's complexity, there arises the question of what a junction is. In the in-situ part of the presented experiment, in the additional task condition, participants were stopped at every junction and asked about the direction toward the destination. A junction was defined based on OSM data at which at least three branches meet. Several times participants were surprised to be stopped again. They would have passed the junction because, in their perception, it was none, or they did not notice that there were other branches to take. In consequence, a real-world study in which participants are not told explicitly to stay at a junction (Cock et al., 2021) is needed. By running such a study, spatial configurations that favor missing a junction could be identified. This insight would help to give better instructions by directing the user's attention to the junction that otherwise would have been missed without assistance. Although the modeled belief vector (the direction in which the user believes the destination is located) worked well for the most part, improvements are now possible as data on the belief vector at each intersection was collected during the experiment (additional task). This improvement will provide more accurate support to users, as the system can better estimate where the user thinks the target is located. This would also decrease the probability of omitting a navigation instruction when actually needed (like in the in-situ study). The knowledge about the belief vector would also improve future simulation studies using FCN.

In the FCN condition, two participants did not arrive because the system estimated the user's current orientation as good enough to leave the user to decide which branch to take. The junction at which this decision was made turned out to be crucial because this was the last junction at which the participant could select which branch to follow before the trial was interrupted and considered a failure. This problem can be avoided by identifying crucial junctions at which assistance is always given, independently of the actual orientation of the user. One possibility would be to use *route-defining locations* as proposed by Teimouri and Richter (2022). These locations define the route and represent important changes in direction, salient landmarks, and relevant streets along the route.

A further step toward personalizing the FCN approach (currently using the sense of direction) is incorporating the user's familiarity with the environment. Analyzing the eye-tracking videos recorded for the TBT and FCN conditions will allow further insights into map use, map interactions, object fixations and visual search behavior. Although the TBT approach has not negatively impacted spatial knowledge acquisition, the map use time may have done so (contrasting results of Stefanucci et al. (2022) and Hejtmánek et al., 2018). Furthermore, less instructions per traversed junction in the FCN condition could have favored forward and backward glances (Brügger et al., 2018).

The presented BeeAR navigation approach is a prototype and comes with a limited graphical user interface. In future work, it can be enriched with additional information (e.g., Matviienko et al., 2022) supporting spatial knowledge acquisition (e.g., highlighting points of interest or minimap - Qiu et al., 2023). Additional information displayed on demand may enhance the user experience and stimulate curiosity (Kota et al., 2010). On the other hand, further visualizations of the destination can be tested. One participant proposed a color-encoded distance indicator to transmit a better understanding of the remaining distance to the destination. Besides displaying the destination, further navigational cues (e.g., compass or current street information) can be added to the AR interface to aid spatial knowledge acquisition (Stefanucci et al., 2022). Another potential enhancement could be achieved by using occlusion for the holograms, i.e., buildings, trees, advertisements, etc., located between the user and the hologram would render parts of the hologram invisible to the user. This cue would address the augmented reality's depth perception problem (e.g., Bodenheimer et al., 2022). The data needed to enable occlusion can be extracted from a digital elevation model. While not looking toward the destination, no information is currently displayed. Off-screen indicators (Gruenefeld et al., 2017) could help the user to improve orientation. The BeeAR approach should be tested in other real-world settings, as this navigation approach might perform worse in areas of different network types (Savino et al., 2022). Although own decisions paired with permanently knowing and seeing the destination location may have led to excellent performance in route retracing and recalling POIs, further research is needed to examine how this knowledge was formed without any map. Furthermore, the learning perspective (egocentric vs. allocentric) should be considered in further analysis (Kuil et al., 2021). Given the novelty of both navigation approaches (FCN and BeeAR), a longitudinal study would probably be more informative, as potential effects of a navigation system may be observable only after the second usage (Kuo et al., 2020).

Combining augmented reality (AR) glasses with a global navigation satellite system (GNSS) receiver allows for a reasonable positional accuracy of the displayed holograms outdoors. Although AR glasses are a valuable research tool, several potential issues regarding their outdoor functionality will be thematized. The weather is probably the most important factor. Of course, it is not possible to run experiments in rainy conditions. On the other hand, perfect weather with sunshine is not good either because the cameras of the AR glasses may get blinded. In consequence, the AR glasses lose their orientation. This causes the previously placed holograms to move in the environment, rendering them useless and requiring a recalibration of the AR glasses. Further potential challenges for AR glasses are fast and natural head movements, as researchers handle the glasses more carefully, avoiding fast head movements. Environments with no salient points may cause orientation loss too. Similar structures can cause the same effect, as the glasses cannot always distinguish well between them. As we can see, there are still many challenges to make AR glasses work robustly outdoors. Solutions to some of them need to be proposed, whereas other challenges can be addressed by custom solutions suitable for wayfinding research (e.g., using sun shades to mitigate direct sunlight). On the other hand, the potential and value of using AR outdoors for wayfinding studies have been shown in Chapter 8.

As discussed, certain limitations apply to this work. Some of these can be overcome by incorporating existing literature, while others require novel approaches and research. Nonetheless, contributions to several ongoing discussions were presented. These discussions include but are not limited to whether pedestrian navigation assistance systems negatively impact spatial knowledge acquisition and whether active users acquire more spatial knowledge than passive users who only follow instructions. Furthermore, I hope this work will initiate a discussion about the importance of route selection in wayfinding experiments and beyond. Finally, the potential of this work to open up new research directions was highlighted, suggesting that impactful research building on this work will be conducted in the future.

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