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Designing and Evaluating an Interactive Dashboard for Communicating Efficiency–Experiential Trade-Offs in Cycling Route-Planning

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Declaration of Originality

I, Margaux Elijah Neri, declare that the thesis titled ”Designing and Evaluating an Interactive Dashboard for Communicating Efficiency–Experiential Trade-Offs in Cycling Route Planning” is entirely my own work, carried out and written independently with guidance from my supervisors. Any assistance I have received is acknowledged, and all sources, whether published or unpublished, are accurately cited. This thesis has not been submitted for any other degree and is not currently under consideration for any other qualification.

Additionally, I declare AI tools were utilized for language editing but not for generating scientific content, research data, or substantive conclusions. All intellectual and creative work, including the analysis and interpretation of data, is original and entirely my own.

Table 1: Use of Generative Artificial Intelligence.

Tasks		**AI tools**
Better understand issues related to the research	✓	ChatGPT 5.2
Summarizing text from bibliography / resources	✓	Scopus AI
Summarizing the method(s) used		
Translating text	✓	ChatGPT 5.2
Grammar check		
Paraphrasing or rewriting text from other people / resources	✓	ChatGPT 5.2, Gemini 3
Coding in R, Python, etc.	✓	ChatGPT 5.2
Getting help on software	✓	Gemini 3
Creating and editing images, maps, videos, etc.		
Data analysis	✓	ChatGPT 5.2
Specify below other tasks not mentioned above:		

Margaux Elijah Neri
Münster, Germany
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Dedication

To my right knee: you fell, but this thesis cycled. Now—run after it!

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Abstract

Cycling route planning involves navigating trade-offs between efficiency-oriented factors, such as travel time and distance, and experiential considerations, including safety, environment, and infrastructure quality. Although these factors are incorporated in many routing systems, there is often limited support for communicating them and allowing users to compare and balance such trade-offs for a more meaningful interpretation of route alternatives. This thesis examines how interaction and visualization design choices, specifically preference-adjustment mechanisms and coordinated visual components, support the communication of efficiency–experiential trade-offs in cycling route-planning dashboards. A design-oriented empirical study was conducted using an interactive dashboard that presents multiple route alternatives with efficiency and experiential metrics. Discrete and continuous modes of preference-adjustment mechanisms, enabling users to specify multi-criteria routing priorities, were evaluated. The dashboard was then assessed through a controlled user study focusing on users' reasoning about trade-offs, perceived cognitive effort, usability, expressiveness, and trust across different commuting contexts. The findings indicate that differences between preference-adjustment mechanisms had limited impact on objective task performance but influenced how users engaged with and interpreted trade-offs. The two mechanisms differed in how cognitively manageable they were perceived to be, with more structured interactions and immediate visual feedback supporting clearer reasoning during exploratory route planning. Furthermore, coordinated map–metric visualizations were found essential in enabling comparison between route alternatives and in understanding the consequences of preference adjustments. No interaction mechanism emerged superior across all evaluated dimensions; instead, the results highlight a trade-off between efficiency-oriented and deliberation-oriented interaction styles. The thesis concludes by deriving design implications for interactive cycling route-planning dashboards and similar geospatial decision-support systems that aim to support transparent and interpretable multi-criteria decision-making.

Keywords: cycling route planning, interactive visualization, trade-offs, preference-adjustment mechanisms, multi-criteria analysis.

Sustainable Development Goal:

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List of Acronyms

API application programming interface

CI confidence interval

CMV coordinated multiple views

DSS decision support systems

GIS geographic information system

HCI human-computer interaction

IP-Dash Intelligent Pendeln Dashboard

IQR interquartile range

MAD median absolute deviation

MCDM multi-criteria decision making

NASA-TLX NASA Task Load Index

OD origin-destination

OE Overall Experience

ORS OpenRouteService

QGIS Quantum Geographic Information System

RQ Research Question

SD standard deviation

SE standard error

SDSS spatial decision support systems

SUS System Usability Scale

TCT task completion time

Chapter 1

Introduction

1.1 Background and Motivation

Cycling is increasingly recognized as a cornerstone of sustainable urban mobility, offering benefits related to health, sustainability, and livability (Goldmann & Wessel, 2021; World Bank, 2025). As cities invest in cycling infrastructure, digital route-planning tools play a growing role in supporting cyclists as they navigate urban environments (Tera, Hadachi, & Pourmoradnasseri, 2025; World Bank, 2025).

Unlike motorized travel, cycling route choices are often shaped by multiple competing factors. In addition to efficiency-focused parameters like travel time or distance, experiential aspects such as safety, environmental aesthetics, and road surface quality play a role (Desjardins et al., 2021; Marquart & Schicketanz, 2022). As a result, cyclists frequently face trade-offs when selecting routes. For instance, detours offering better comfort and environmental quality may be favored at the expense of longer travel times (Hardinghaus & Nieland, 2021; Ludwig, Lautenbach, Schömann, & Zipf, 2021; Nawrath, Kowarik, & Fischer, 2019). However, mainstream navigation systems primarily optimize for efficiency, failing to capture the full spectrum of factors influencing cycling decisions in real urban contexts (Cruz et al., 2020; Wage et al., 2020).

Supporting diverse decision criteria requires not only better data, but also interfaces that allow users to clearly understand and modify trade-offs. Interactive geospatial dashboards integrate maps, metrics, and interactive controls to facilitate interpretive processes. In decision-support contexts, these coordinated visual components allow users to explore alternatives, observe changes across representations, and reason about trade-offs more effectively than static interfaces (Hakanen et al., 2022; Milutinovic & Seipel, 2018; Nadj, Maedche, & Schieder, 2020). The effectiveness of such dashboards depends not only on the data they present, but also on how interface design shape user interactions with complex information (Yigitbasioglu & Velcu, 2012).

As cycling is widely advocated as a daily mode of transport, it becomes increasingly important to design systems that cater to the specific needs of users (Marquart & Schicketanz, 2022). However, there remains limited empirical understanding of how different preference-adjustment mechanisms and coordinated visualizations support the communication of efficiency–experiential trade-offs in cycling route planning. In particular, the interplay between interaction design elements and user reasoning and perception in this context remains unclear. Bridging this gap is essential to evolve cycling navigation interfaces and, more broadly, for advancing multi-criteria decision-support systems that rely on interactive preference articulation. This study investigates these dynamics from the perspective of cyclists interacting with alternative preference-adjustment mechanisms.

1.2 Problem Statement and Research Gap

Cycling route planning involves navigating trade-offs between efficiency and experiential considerations. In this thesis, the term experiential factors refers both to the physical characteristics of the environment (e.g., greenery, noise, traffic exposure) and to the subjective riding experience (e.g., perceived comfort, safety, aesthetic appeal, and stress levels), as distinct from efficiency metrics such as travel time or distance. While many routing systems incorporate these criteria, there is often limited support for an interactive means to express user priorities that influences route recommendations (Barth, Funke, & Storandt, 2018).

Prior research on cycling route planning has focused largely on routing algorithms, identifying and measuring factors that influence route choice, and wayfinding platform development (Barth et al., 2018; Huang, 2025; Juarez et al., 2023; de Matos et al., 2021); however, there is relatively limited attention to interaction design, specifically on how users engage with preference-adjustment mechanisms or interpret metric comparisons within dashboard interfaces (Fuest et al., 2023; Nadj et al., 2020). As such, there is a lack of empirical evidence on how interaction and visualization design choices support the communication of efficiency-experiential trade-offs. Consequently, cyclists may interact with routing systems without clear understanding of how recommendations are generated.

These gaps intersect into an open question of how coordinated visual components and preference-adjustment mechanisms can be designed and evaluated to better communicate efficiency–experiential trade-offs in cycling route-planning dashboards. This study addresses this by adopting a design-oriented, empirical approach to examine how interaction and visualization design choices support the communication of efficiency–experiential trade-offs in cycling route-planning dashboards.

1.3 Research Objectives

The primary objective of this thesis is to design and empirically evaluate an interactive, multi-criteria cycling route-planning dashboard that communicates efficiency–experiential trade-offs, focusing on how interaction and visualization design choices influence users' interpretation of these relationships:

To achieve this, the following specific objectives are addressed:

1. To explore and assess alternative preference-adjustment mechanisms and visualization strategies through preliminary user research, in order to inform the design of the main experimental dashboard prototype.

2. To design an interactive cycling route planning dashboard that integrates coordinated visual components with preference-adjustment mechanisms to support exploration of efficiency–experiential trade-offs.

3. To evaluate differences in cognitive effort, usability, and perceived expressiveness associated with preference-adjustment mechanisms when specifying multi-criteria route preferences.

4. To examine how coordinated visual components and preference-adjustment mechanisms shape users' understanding, trust, and perceived usefulness of route recommendations across different commuting contexts.

5. To derive design implications for interactive cycling route-planning dashboards that support the communication of trade-offs, with potential relevance to similar mobility and spatial decision-support systems.

1.4 Research Questions

To examine how interaction and visualization design choices support the communication of efficiency–experiential trade-offs in cycling route planning, this study is guided by the following research questions:

1. How do different preference-adjustment mechanisms shape users' reasoning on efficiency-experiential trade-offs in cycling route planning?

2. To what extent do different preference-adjustment mechanisms vary in terms of cognitive effort, usability, and expressiveness when cyclists specify multi-criteria route preferences?

3. How do the coordinated visual components of the dashboard and the preferences adjustment mechanisms influence the' understanding of cyclists about trade-offs, trust, and perceived usefulness in different commuting contexts?

1.5 Scope and Assumptions

This study investigates how different preference-adjustment mechanisms shape user reasoning and experience in multi-criteria cycling route planning. The scope of the study defined in this section clarifies the conditions under which the findings should be interpreted.

The study uses spatial data and base maps from Münster, a city in Germany with well-developed biking infrastructure and a strong cycling culture (PTV Transport Consult GmbH, 2022). This site choice was due to the availability of detailed cycling network data and experiential factor information, as well as the relevance of the study context to the participant pool. While Münster-specific data were used to ground the prototype in a realistic setting, the study does not aim to produce city-specific routing insights. The city merely serves as a realistic urban cycling context to situate the prototype within an infrastructure-rich environment that enables meaningful interaction and interpretation during evaluation.

Participants were active urban cyclists who regularly commute by bicycle with a baseline literacy on digital navigation tools. Differences in cycling expertise were not treated as an experimental variable, as the focus of the study is on interaction mechanisms rather than user typologies.

The experimental tasks were designed as short, exploratory commute routing scenarios. Tasks were hypothetical but realistic, and no real-world navigation was involved. The experiment was conducted face-to-face in an indoor laboratory setting, without real-time constraints or external environmental pressures. As such, findings reflect decision-making during exploratory planning rather than in situ navigation.

The evaluated prototype used predefined routing alternatives and a fixed set of experiential factors – safety, environment, and infrastructure. All routing alternatives and scoring logic were fixed, with personalization limited to preferences explicitly adjusted by the participants.

The findings in this study are intended to generalize preference-adjustment mechanisms and interaction principles within cycling route-planning dashboards, with potential relevance to other spatial decision-support contexts that involve multi-criteria trade-offs.

Chapter 2

Literature Review

Cycling route planning involves more than identifying the fastest or shortest path between two locations. Efficiency is often negotiated with a wide range of other factors such as safety, greenery, and noise exposure. As such, cycling navigation can be understood as a form of spatial decision-making, where users must assess multiple competing factors when selecting a route.

Addressing this decision context requires drawing from three intersecting domains of literature: cycling route choice, spatial decision support systems (SDSS), and human-computer interaction (HCI). Cycling literature provides empirical evidence that non-efficiency considerations play a meaningful role in cyclists' route preferences, SDSS explains conceptual foundations for structuring and comparing alternatives across multiple criteria, and HCI contributes insights on trade-off communication and how users interact with decision-support interfaces.

Accordingly, this review follows a design-oriented, thematic approach, focused on extracting design-relevant insights on interaction strategies and perceptual outcomes. Emphasis is placed on exploratory route planning, preference-adjustment mechanisms, and perceptual outcomes such as comprehension, cognitive load, perceived control, and trust. Algorithmic routing optimization, real-time navigation, and system performance benchmarking are beyond the scope of this review.

The scope of this review moves from foundational SDSS and dashboard concepts into the specific trade-offs of cycling route-choice, focusing on how interactive visualizations can help users navigate these complex decisions. It then establishes a methodological framework through HCI and SDSS evaluation techniques. This chapter connects key streams of work in these fields in the context of everyday cycling navigation and identifies the gaps that motivate the present study.

2.1 Spatial Decision Support Systems and Dashboards: Design Concepts

SDSS evolved from traditional decision support systems (DSS) by integrating geographic data, spatial analysis, and visualization to support problem solving that involves multiple spatial criteria (Malczewski, 2006). A defining feature of SDSS is the use of multi-criteria decision making (MCDM), which makes it particularly relevant for decision contexts where trade-offs are involved.

SDSS have been widely adopted in domains where decisions are typically institutional such as land suitability analysis (Buehler & Wright, 1991), environmental impact prediction (Johnson, Low-Choy, & Mengersen, 2012), and disaster and hazard management (Grayman, Heath, & Males, 1992; Maulana, Syaufina, Prasetyo, & Aidi, 2020). While these applications demonstrate the value of SDSS for complex spatial problems, they differ substantially from everyday navigation contexts, where decisions are made at the individual-level. As a result, the direct applicability of SDSS approaches remain limited particularly in the context of everyday mobility and navigation.

Dashboards have increasingly been adopted as interfaces for SDSS, particularly in urban and smart-city applications. These systems can enhance transparency by supporting comparisons across multiple indicators. However, most of these systems are critiqued for remaining top-down and managerial, which constrains user-centred decision-making (Alsayahani, 2023). As such, while dashboards can make complex information visible, they do not necessarily facilitate deeper engagement with trade-offs or enable users to actively shape decisions according to their own priorities.

A central challenge in SDSS and dashboard design is communicating complexity without overwhelming users. Research shows that presenting multiple criteria can lead to cognitive overload, while highly automated decision-support features may improve efficiency at the cost of reduced situational awareness (Nadj et al., 2020; Sudár & Csapó, 2024). Furthermore, studies highlight challenges in decision transparency, stressing that dashboards must make data sources, trade-offs, and uncertainties visible to foster user trust (Hoffenson et al., 2023; Matheus, Janssen, & Maheshwari, 2020). In response to these issues, design-oriented approaches within SDSS and dashboard research have emphasized the importance of purposeful design strategies. Examples include storytelling dashboards that structure models around the decision-maker's mental model (Lavalle et al., 2025) and incorporating public participation (Bastos, Fernández-Caballero, Pereira, & Rocha, 2022; Vornhagen, Zarrouk, Davis, & Young, 2021).

In mobility contexts, SDSS concepts are relevant because route choice inherently involves diverse trade-offs including personal and social values. Yet, most mainstream navigation systems communicate route options primarily in efficiency-focused parameters like time and distance. Bridging this gap requires rethinking dashboards not only as information displays but as interactive decision-support environments where users can visualize and prioritize the factors that matters most to them.

2.2 Cycling Route Choice and Experiential Factors

Route choice models traditionally prioritize efficiency factors, particularly distance and travel time, because these are easy to measure and integrate into routing algorithms. However, growing evidence shows that cyclists also select routes based on qualitative attributes that contribute to comfort, safety, and overall trip satisfaction.

Safety is among the most influential experiential factors. Routes with lower motor traffic volumes, dedicated cycling infrastructure, and safer intersections are favored, even when they deviate against directness (Gössling, Humpe, Litman, & Metzler, 2019; Li, Ji, & Wang, 2019). Environmental quality also plays a role. Greener, cleaner, and calmer paths, though often deterring from efficiency-oriented routes, enhance the cycling experience (Anowar, Eluru, & Hatzopoulou, 2017; Gössling et al., 2019; Ludwig et al., 2021; Park & Akar, 2019; Xiao, Chen, Zhang, & Gong, 2025; Q. Zhang, Rui, & Wu, 2024). These priorities are further shifted by contextual factors such as topography, weather conditions, and trip purpose. Cyclists tend to avoid steep gradients or precipitation (Berghoefer, Miether, & Vollrath, 2025; Nawrath et al., 2019; Schmitt et al., 2023), and are prone to shift priorities between aesthetic enjoyment and network efficiency (Łukawska, Paulsen, Rasmussen, Jensen, & Nielsen, 2023). Taken together, cycling navigation and route choice are uniquely driven by perceived safety, mental comfort, and environmental aesthetics, as they heavily influence a cyclist's willingness to accept detours for a more physically manageable and low-stress journey.

Despite recognition of these experiential factors, they have rarely translated into user-facing decision-support tools and are weakly integrated in most routing applications (Ludwig et al., 2021). As a result, cyclists are often unable to explicitly adjust the importance of experiential factors nor explore how different priorities affect route recommendations.

In sum, literature suggests that cycling route choice is inherently multi-criteria and value-driven, involving the negotiation between efficiency and experiential considerations. Supporting such decision-making requires interfaces that go beyond presenting efficiency-optimized routes to enable users to understand and actively shape these trade-offs. This observation motivates the examination of visualization and interaction strategies for communicating trade-offs in cycling route-planning dashboards, which is the focus of the succeeding section.

2.3 Visualization of and Interaction with Trade-offs

Decision-making in complex domains often requires balancing multiple competing factors. When choices involve trade-offs, users must understand not only individual criteria but also how changes in priorities affect outcomes (Hakanen et al., 2022). Without appropriate support, such trade-off reasoning can be cognitively demanding.

Visualization and interaction play a central role in supporting trade-off reasoning in DSS (Milutinovic & Seipel, 2018; Nadj et al., 2020). Visualization can make abstract trade-offs more interpretable, while interaction enables dynamic exploration of preference-to-outcome relationships. However, when visualization is presented without meaningful interaction, it often remains descriptive rather than actively supporting decision-making.

A key aspect of interaction in multi-criteria DSS is the mechanism through which users express their preferences. These preference-adjustment mechanisms can be broadly categorized as discrete or continuous. Discrete preference-adjustment mechanisms are often associated with lower interaction effort and faster use, as they limit the range of possible inputs and reduce the need for fine-grained calibration. An example is bundling weights in preset profiles (Looney & Hardin, 2015; Moody, 2004) or clear binary selection via checkboxes (Conrow et al., 2023). In contrast, continuous mechanisms provide greater expressive power, allowing users to specify nuanced prioritizations across criteria. One common form is interactive sliders (Kleemann & Ziegler, 2020; Carvalho, Belo, & Silva, 2019), but studies show they can increase cognitive load when many factors are presented simultaneously (Pignatiello, Daly, Demaree, Moore, & Hickman, 2019).

Another strand of research focuses on visual metaphors for representing multi-criteria trade-offs. Common forms like tables, bar charts, hexagon diagrams, and Pareto frontier visualizations have been explored in domains such as clinical decision support and environmental planning (Lotov, 2007; Nadj et al., 2020; Rees et al., 2022). While these examples illustrate general principles for making trade-offs visible, their direct application to mobility and routing contexts is not straightforward. Due to differences in testing conditions, such approaches offer conceptual guidance rather than ready-made solutions in cycling navigation contexts.

A persistent challenge in trade-off visualization is achieving user comprehension and trust. HCI research highlights that complex or abstract visual models often have higher accuracy but are less interpretable, leading to trust issues (Goethals, Martens, & Evgeniou, 2022). Conversely, overly simplified models risk hiding important information and sacrificing some accuracy (Assis, Véras, & Andrade, 2023). Balancing comprehensibility, accuracy, and usability is therefore a key design challenge.

Within the context of routing and mobility, however, visualization remains relatively underdeveloped. Most navigation systems display routes as simple polyline overlays on maps, accompanied by utilitarian attributes such as travel time and distance (Amirgholy, Golshani, Schneider, Gonzales, & Gao, 2017; Siriaraya et al., 2020). Some research prototypes have experimented with enhanced visualizations such as coloring routes based on safety scores (Shkedova, Fuest, & Sester, 2024) or adding side panels with factor comparisons (Boriboonsomsin, Dean, & Barth, 2014), but these innovations have not been widely adopted (Amirgholy et al., 2017).

In summary, existing research provides valuable design strategies, but most applications remain outside the domain of mobility. Cycling navigation presents a distinctive case where users make frequent, time-sensitive decisions, and where experience-focused factors are as critical as efficiency. Adapting established visualization and interaction approaches into this context requires careful consideration to support transparent and interactive weighting of factors without overwhelming the user.

2.4 Evaluation Approaches in HCI and SDSS

Evaluation is a critical component of DSS, as it validates not only the technical performance of a system but also its usability, effectiveness, and impact on decision-making. This perspective is particularly relevant for systems that aim to support trade-off reasoning, where the quality of interaction and communication can be as important as the underlying computational logic.

Typical approaches in HCI include think-aloud protocols, where participants verbalize their reasoning while interacting with a prototype (Capdevila, Saltiveri, Garrido, Müller, & Ruas, 2021), and semi-structured interviews to gather user perception of usability, satisfaction, and cognitive load (Köles, 2017; Ogunyemi, Lamas, Lárusdóttir, & Loizides, 2019). These qualitative evaluations are often combined with quantitative methods (Assila, de Oliveira, & Ezzedine, 2014; Yoon, 2023). The System Usability Scale (SUS) remains one of the most widely used measures of usability (Adapa et al., 2021). Another standardized assessment metric is the NASA Task Load Index NASA Task Load Index (NASA-TLX), which evaluates perceived cognitive workload after task completion (L. Zhang & Cui, 2022). Recent HCI studies have expanded the evaluation criteria to gauge trust and explainability using user survey ratings and experimental comparisons (Alhasan & Alnanih, 2025; Bhat, 2025).

In SDSS research, evaluation commonly focuses on decision quality and effectiveness, which encompasses verification, validation, user acceptance, and system performance (Cohen, Cohen, Broday, & Timar, 2008; Reynolds, Hessburg, & Bourgeron, 2014). Methods range from controlled experiments, presenting users with decision scenarios under different system conditions, to case studies and participatory workshops that assess real-world relevance (He & Sun, 2015).

A recurring challenge in both HCI and SDSS evaluations is the trade-off between depth and feasibility (Lazar, Feng, & Hochheiser, 2017). Large-scale field studies provide rich, generalizable insights but are often time-consuming and resource intensive. Smaller laboratory studies, in contrast, are easier to manage but may limit external validity. Scholars therefore emphasize methodological triangulation, where controlled experiments, observational methods, and qualitative feedback are integrated to capture both usability and decision outcomes (Bekhet & Zauszniewski, 2012; Durif-Bruckert et al., 2015).

This thesis draws on evaluation perspectives from HCI and SDSS to examine how different interaction mechanisms shape trade-off reasoning in cycling navigation. Rather than focusing on routing optimality or system performance, the evaluation centers on perceptual and experiential outcomes such as trade-off clarity, perceived control, cognitive workload, and trust in route recommendations.

2.5 Synthesis and Research Gap

The reviewed literature establishes that cycling route planning is not purely oriented in efficiency, rather it constitutes a value-driven multi-criteria decision process. Cyclists consider experiential factors such as safety, greenery, and noise in addition to time and distance. In parallel, SDSS research lays the foundation for structuring decisions involving multiple criteria and trade-offs, whereas HCI research provides insights on the role that visualization and interaction design play in shaping how users understand, engage with, and trust DSS.

At the intersection of these domains remain some important gaps. While experiential factors are well established in cycling research, their explicit integration into user-facing navigation tools remains limited; hence, cyclists are often constrained to actively negotiate trade-offs or tailor route choices to their preferences. Concurrently, the direct applicability of visualization and interaction strategies to cycling navigation remains underexplored. There is limited empirical evidence on how different preference-adjustment mechanisms shape users' understanding of trade-offs, perceived control over decision-making, and confidence in their choices. In addition, existing studies place a secondary focus on examining how users interact with and interpret trade-offs through interface design. Yet these are critical for exploratory decision-making contexts, where users must make sense of competing criteria rather than follow a single optimal solution.

In response to these gaps, this thesis addresses the design and evaluation of a cycling route-planning dashboard that features user interaction with efficiency-experiential trade-offs. Specifically, it empirically examines how different preference-adjustment mechanisms affect users' comprehension of trade-offs, perceived control, cognitive load, and trust in route recommendations. The study contributes empirical insights into how interaction design can support more transparent and user-centered decision-making in cycling route planning.

The synthesis of the literature thus motivates the methodological approach to investigate how interaction mechanisms influence users' experiences of trade-off negotiation in cycling navigation dashboards.

Chapter 3

Methodology

3.1 Research Design and Approach

3.1.1 Design Expectations and Hypotheses

Prior research on user preferences and performance with various control interfaces and dashboard designs suggest that different forms of interaction mechanisms influence task performance, cognitive load, and decision-making (Bae, Lyu, Lee, & Yun, 2025; Lanz & Provins, 2015; Priorelli & Stoianov, 2024). Discrete controls are advantageous for precise, decision-based tasks, while continuous controls facilitate more dynamic exploration and excel in tasks requiring smooth adjustments. In the context of cycling route planning, the following outcomes are expected:

- $\mathbf{H_{1a}}$: It is expected that continuous preference-adjustment mechanisms encourage more reflective reasoning about efficiency–experiential trade-offs than discrete mechanisms.

- $\mathbf{H_{1b}}$: It is expected that discrete preference-adjustment mechanisms promote simplified and precise reasoning during route comparison.

Accordingly, design expectations concerning cognitive effort, usability, and expressiveness across preference-adjustment mechanisms are formulated. Existing research highlights that interfaces offering greater expressiveness may impose higher cognitive demands, while simpler interfaces often reduce interaction effort (Barth et al., 2018; de Lima da Silva et al., 2024; Hrncir et al., 2014; Pommeranz et al., 2012).

- $\mathbf{H_{2a}}$: It is expected that continuous preference-adjustment mechanisms will be associated with higher perceived cognitive effort than discrete mechanisms.

- $\mathbf{H_{2b}}$: It is expected that preference-adjustment mechanisms that provide clearer feedback on how changes in user preferences affect displayed route alternatives will be perceived as more usable.

- **H_{2c}**: It is expected that a trade-off between ease of use and expressiveness will be involved, such that discrete mechanisms are perceived as easier to use, while continuous mechanisms are perceived as better suited for detailed customization of preferences.

On the dashboard level, research in spatial decision systems suggests that visualization of spatial context play an important role in shaping users' perceptions of safety, comfort, and route attractiveness (Hu et al., 2025). In addition, transparency in how user adjustments influence outcomes has been linked to increased trust and perceived usefulness (Hardinghaus & Papantoniou, 2020; Lilasathapornkit et al., 2025). In this sense, coordinated visual components and preference-adjustment mechanisms are expected to support users differently depending on the context in which route planning occurs.

- **H_{3a}**: It is expected that coordinated visual components combined with preference-adjustment mechanisms will boost users' understanding of efficiency–experiential trade-offs.

- **H_{3b}**: It is expected that greater transparency on preference–to-outcome relationships is expected to be associated with higher trust in recommended routes.

- **H_{3c}**: It is expected that the perceived usefulness of the dashboard will vary across commuting contexts, with more expressive mechanisms being valued in unfamiliar scenarios.

The succeeding section details the study design, experimental procedure, data collection instruments, and analytical approach adopted to evaluate these hypotheses.

3.1.2 Methodological Framework

In this study, the research questions address performance, usability outcomes, and how users reason about trade-offs when interacting with alternative preference-adjustment mechanisms. As such, integrating methods is necessary to capture the full decision-making process (Hakanen et al., 2022; Lazar et al., 2017). Quantitative measures allow systematic comparisons of interaction behavior, perceived usability, and workload, while qualitative responses provide insight into reasoning strategies, interpretation of visual feedback, and contextual framing of preferences (Nadj et al., 2020). Triangulation across these methods enables the integration of behavioral, perceptual, and interpretive perspectives, allowing to investigate patterns or differences, as well as how and why they arise (Lazar et al., 2017).

Accordingly, this research employs a two-stage, mixed-methods design, transitioning from exploratory design-filtering to a controlled experimental evaluation, to investigate how interaction design in cycling route planning dashboards support the communication of efficiency and experiential trade-offs:

1. **Preliminary User Research**: An exploratory online study was conducted to evaluate various metric display formats, preference-adjustment mechanisms, and visualization elements. This stage narrowed the design space by identifying configurations that respondents found most interpretable, trustworthy, and useful for route comparison. These insights directly informed the design of the experimental dashboard configuration used in the following stage.

2. **Main Experiment**: A controlled laboratory experiment was conducted using the finalized dashboard prototype. The focus was on evaluating the dashboard as a research artifact to observe user comprehension and decision-making strategies across two alternative preference-adjustment mechanisms, the checkboxes and the slider.

Objective interaction logs and standardized scales were combined with qualitative thematic analysis. This allowed for triangulation, where qualitative insights explained the patterns in the quantitative data.

The overall research process, from initial data preprocessing to the final experimental evaluation, is illustrated in Figure 3.1.

3.2 System Architecture and Data Sources

The study was situated in Münster, Germany, a city globally recognized for its cycling infrastructure. This choice of study area was not for location-specific analysis, rather to provide a realistic urban cycling environment and authentic map layouts for the experimental tasks.

To ensure high-performance interaction during the experiment, all route data were pre-processed and pre-loaded into the prototype. The data pipeline integrated two primary sources:

- **Efficiency Metrics**: Route alternatives and geometries were generated using the OpenRouteService (ORS) application programming interface (API) and cycling paths from the Intelligent Pendeln Dashboard (IP-Dash).

- **Experiential Scores**: Safety, Environment, and Infrastructure indicators were derived from IP-Dash, a bikeability dashboard which takes into account the same

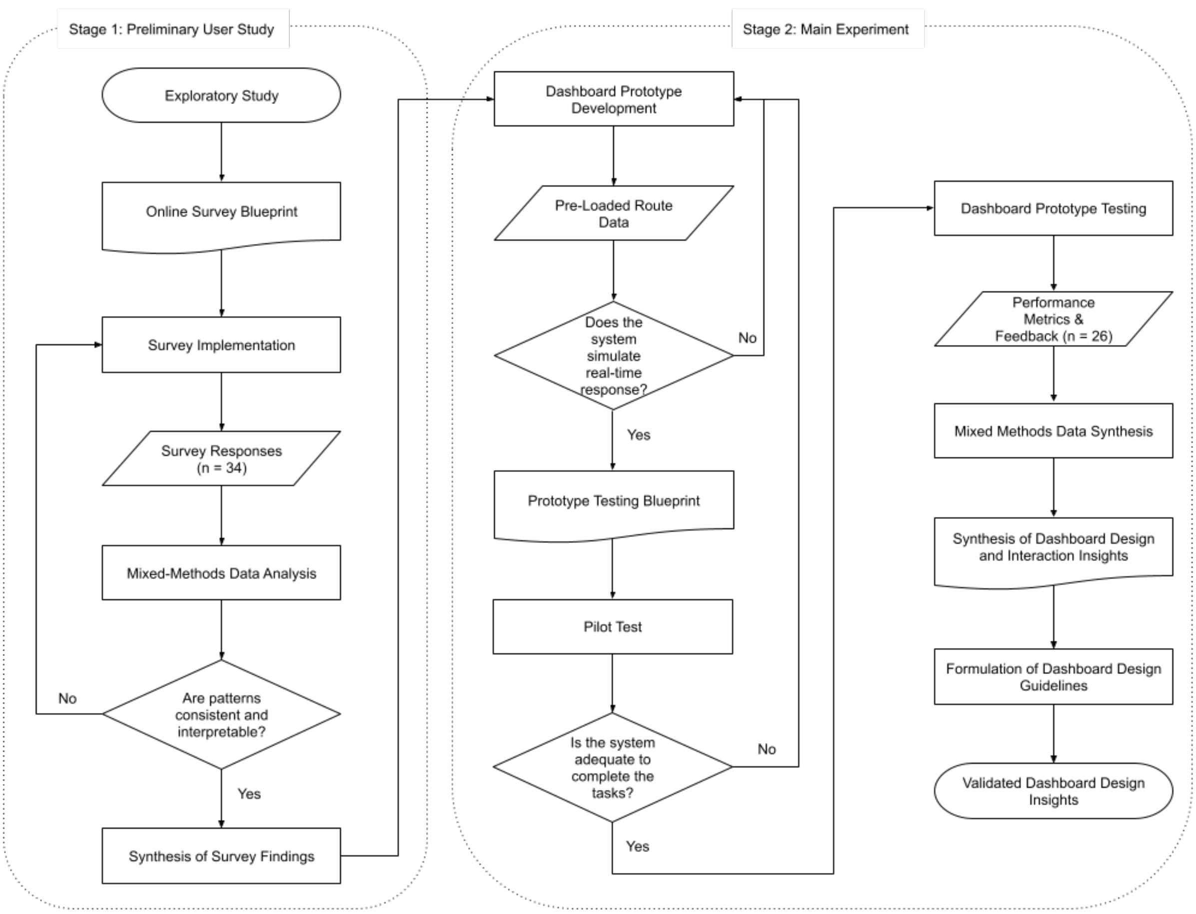


Figure 3.1: Overview of the methodological workflow.

categories for calculation. Geospatial workflows in Quantum Geographic Information System (QGIS) and Python were used to aggregate segment-level indicators into the route-level attributes. These scores were manually adjusted to accentuate comparative differences and ensure that trade-offs were perceptible.

The experimental dashboard was implemented as a desktop-based interactive prototype. To isolate interaction effects from routing computation, the system did not perform real-time optimization. Instead, user interactions – such as adjusting the slider or toggling a checkbox – triggered deterministic updates to the route rankings and visual encodings.

The software environment included:

- **Dashboard Development**: The dashboard's visual design and interactive components were prototyped in Figma and then transformed into a functional, interactive experience using Figma Make.

- **Survey Instruments**: Administered online via Google Forms for standardized data entry.

- **Analysis Environment**: Quantitative and qualitative data processing were performed in R (RStudio version 2024.12.1+563). Microsoft Excel was employed to cross-validate statistical results.

3.3 Preliminary User Research

An exploratory online study (n=34) was conducted to narrow the design space for the experimental dashboard. The primary objective was to evaluate user comprehension, trust, and preference across alternative visualization formats and interaction controls.

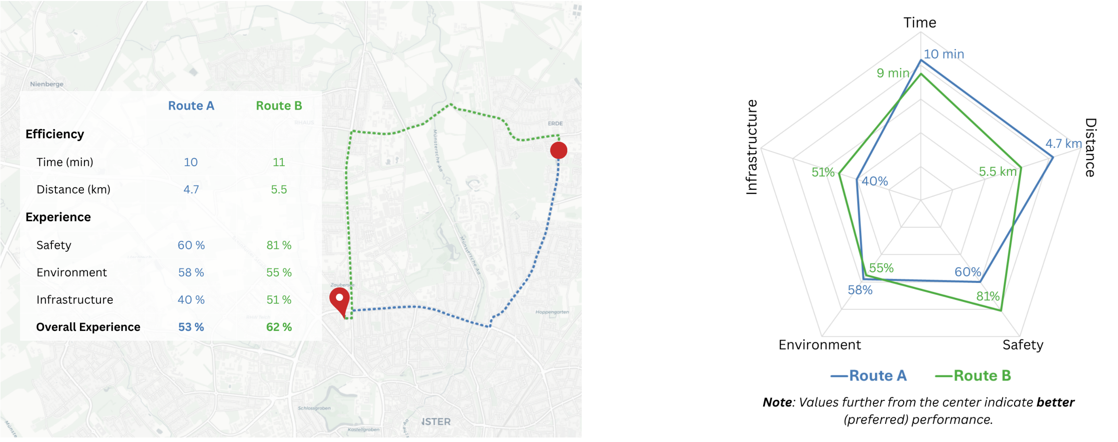
Following the online exploratory process documented by Lazar et al. (2017), participants were recruited using a convenience sampling strategy, through academic networks and personal contacts. Initial invitations were distributed to individuals known to regularly commute by bicycle, who were then encouraged to share the survey within their networks (snowball recruitment). This recruitment approach was considered appropriate for the exploratory aims of the preliminary study, which sought to inform subsequent prototype design rather than to draw population-level conclusions . The eligibility criteria included using cycling as a means of commuting and familiarity with digital navigation tools. No restriction were placed on age or geographic location. The study was then administered as an online survey using Google Forms, allowing to reach a broader participant base and reduce bias in the prototype development process. The survey was voluntary, uncompensated, and took approximately 12–15 minutes to complete. Appendix A presents the full list of the online survey items.

The survey utilized mixed methods, presenting participants with 6 visualization conditions. These combined three formats (table, bar charts, and spider diagram), which are widely documented in decision-support contexts (Lotov, 2007; Nadj et al., 2020), to display attribute indicators. These indicator visualization forms were tested against two spatial contexts (with map vs. without map) to identify which combinations best support clarity, comparability, and perceived usefulness during route evaluation. The selection of attributes used in the stimuli is widely documented as valued by cyclists in navigation contexts (Gössling et al., 2019; Ludwig et al., 2021):

- **Efficiency Metrics**: time, distance
- **Experiential Factors**: safety, environment, and infrastructure

Additionally, three preference-adjustment mechanisms (checkboxes, preset categories, and slider) were evaluated. These mechanisms represent commonly used discrete and continuous modes of preference selection in interactive systems and span different levels of preference granularity and user effort, allowing the study to examine how coarse versus fine-grained preference adjustment shapes perception and decision-making (Conrow et al., 2023; Kleemann & Ziegler, 2020; Looney & Hardin, 2015).

Figures 3.2 - 3.4 depicts representative stimuli used in the preliminary survey.



(a) table with map

(b) spider diagram without map

Figure 3.2: Representative static KPI visualizations with and without a map.

Figure 3.3: Representative static visualization of slider mechanism and bar charts.

A within-subjects survey design was employed, which allowed effective control for individual differences with a small sample size (Field, 2018).To mitigate learning and fatigue effects, the presentation order was counterbalanced across two versions of the survey.

The findings of this preliminary user research stage provided the empirical basis for the final dashboard configuration. Appendix B details the results and analysis that lead to the following design decisions:

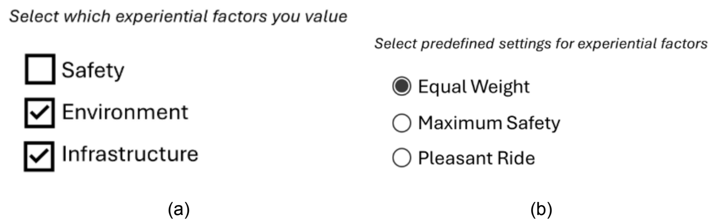


Figure 3.4: Visualizations of mechanisms: (a) checkboxes and (b) preset categories.

- **Visualization Choice**: Bar charts were selected over tables and spider diagrams because they were rated highest for clarity in multi-metric comparisons. Participants noted that bar charts made trade-offs between experiential factors easier to interpret at-a-glance.

- **Map Presence**: Quantitative ratings and open-ended feedback confirmed that the presence of a map significantly improved user confidence and spatial comprehension. Consequently, a map was integrated as a core component of the main experiment.

- **Control Filtering**: While the slider was valued for its expressiveness and the checkboxes for ease of use, the preset-based mechanism was frequently cited as confusing or restrictive. Hence, the preset-based mechanism was excluded to focus the main experiment on the tension between high-control (slider) and low-effort (checkboxes) interactions.

3.4 Dashboard Design and Interaction Mechanisms

Following the iterative refinement from the preliminary study, the experimental dashboard was finalized as a mid-fidelity prototype that emphasizes functional interactions rather than aesthetic finish (McCurdy, Connors, Pyrzak, Kanefsky, & Vera, 2006).

The dashboard presents the same distinct types of route attribute data as the preliminary research: efficiency (time, distance) and experiential (safety, environment, and infrastructure). To prevent cognitive confusion, these were displayed separately. Efficiency metrics were presented as static numeric labels near each route on the map, as they represent 'cost,' where lower is better. Experiential factors, complemented by an aggregate measure termed *Overall Experience (OE) score*, are visualized using horizontal bar charts, where higher scores indicate greater 'benefits.' These bars were grouped by route option rather than by indicator to support at-a-glance pairwise comparisons (Etemadpour, Linsen, Paiva, Crick, & Forbes, 2016). The colors of the bars followed standard cartographic conventions for intuitive association (Brewer, 2005), as illustrated in Figure 3.5.

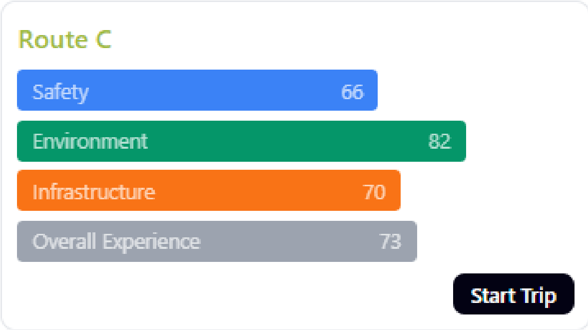


Figure 3.5: Experiential factors visualization. Horizontal bar charts grouped by route. Color coding distinguishes the factors: blue (safety), green (environment), orange (infrastructure), and gray (OE score).

Experiential factor values were based on IP-Dash scores but rescaled to exaggerate relative differences between routes. This was done to enhance perceptual clarity and support participants' reasoning about trade-offs within the limited duration of the experimental tasks.

The main experiment evaluates two alternative preference-adjustment mechanisms. These represent the primary independent variables and differ in how they constrain user input and calculate the OE score. Table 3.1 summarizes the differences between the checkbox- and slider-based mechanisms.

Table 3.1: Comparison of the preference-adjustment mechanisms

Feature	**Checkboxes**	**Slider**
Logic	discrete selection	continuous weighting
User Agency	binary (inclusion / exclusion)	fine-grained tuning
Scoring Calculation (OE)	simple average of all selected factors	weighted average based on user-assigned values
Constraint	all selected factors are weighted equally	sum of factor weights always totals 100%

(a) checkboxes (b) slider

Figure 3.6: Preference-Adjustment Interfaces. The panels show (a) the discrete checkboxes mechanism where selected factors are weighted equally and (b) the continuous slider mechanism where weights must total 100%.

The dashboard allows users to toggle between two optimization modes, which fundamentally change how routes are ranked and presented:

- **Optimize by fastest time**: This mode follows traditional routing logic, ordering routes solely based on the shortest travel time.

- **Optimize by my preferences**: This mode disregards travel time and ranks routes based on the OE score. The computation for this metric is described in Table 3.1

By switching between these modes, users can explicitly compare the most efficient route against their most preferred experiential route. The system generates the routes based on the optimization settings after the user clicks *Apply* button. By default, only the top two ranked routes are displayed to minimize cognitive effort (Hakanen et al., 2022). Users can expand this view via the *Show all routes* toggle to see the full list of alternatives in their current ranked order.

A coordinated multiple views (CMV) layout is utilized, ensuring that all information is consolidated on a single screen (Conrow et al., 2023; Roberts, 2007).To support decision-making across geographical and attribute spaces (Milutinovic & Seipel, 2018; Roberts, 2007), a two-way linked highlighting system is implemented:

- **Spatial Linking**: Hovering over any bar chart element highlights the corresponding route on the map, and hovering over a route path or label highlights its corresponding bar chart.

- **Attribute Linking**: Hovering over a specific bar (e.g., ”Safety”) in one route’s chart simultaneously highlights all ”Safety” bars across all other visible charts, facilitating rapid cross-comparison.

Finally, concise definitions for experiential terms are provided via tooltips, accessible by hovering over information icons. Figures 3.7 and 3.8 show overviews of the integrated research artifact. For reference, an interactive version of the prototype is archived and made available in Appendix C.

3.5 Main Experimental Design

The main experiment employed a single-factor, within-subjects design, in which each participant completed route-choice tasks using both the checkboxes and slider mechanisms. This design ensured that differences in user behavior could be attributed to the interaction mechanism rather than individual user traits (Field, 2018).

3.5.1 Participants and Recruitment

A total of 26 participants were recruited through academic networks and convenience sampling via direct invitation. To ensure the sample represented the target user group, the following inclusion criteria were applied:

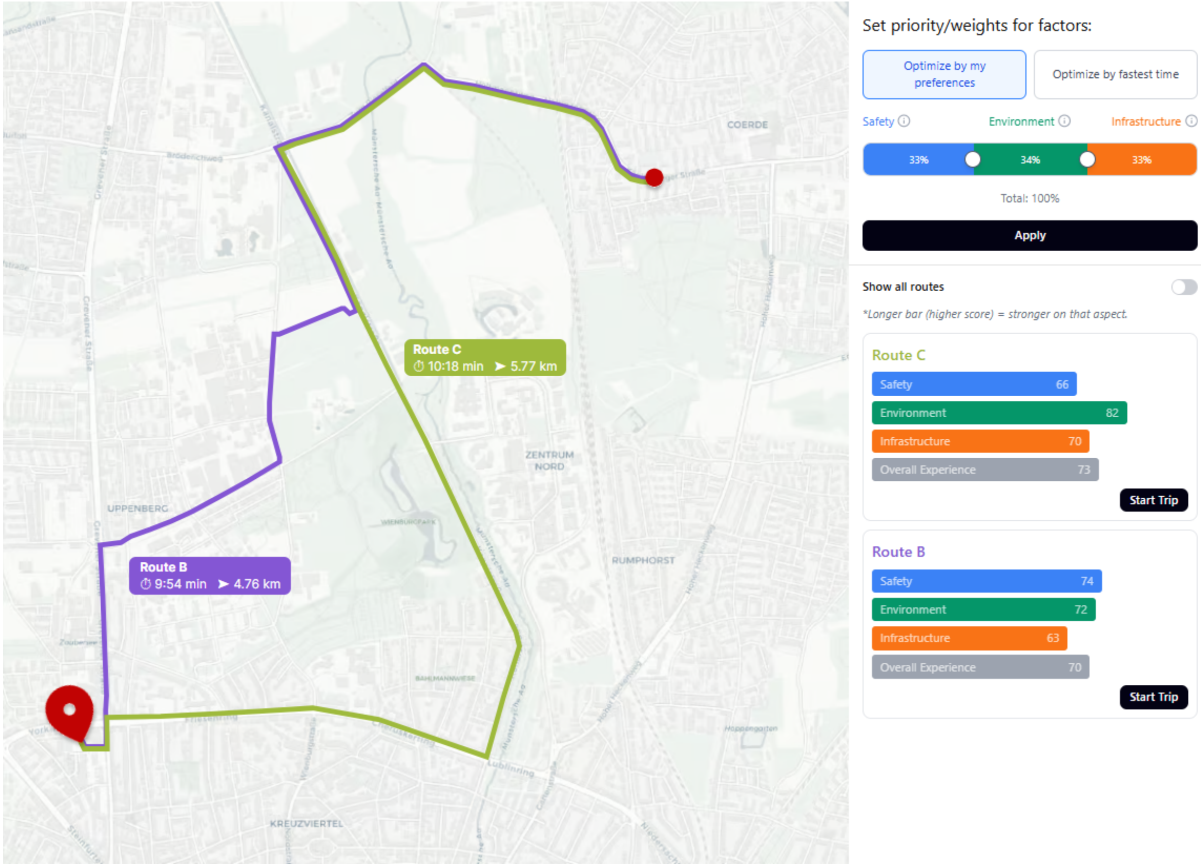


Figure 3.7: Dashboard overview using the slider mechanism and optimized by user preferences.

- Active Cyclists: Participants must be commuting via bicycle in urban environments at least occasionally.
- Navigation Literacy: Familiarity with digital navigation tools (e.g., Google Maps).

The sample included a diverse range of cycling frequencies and varying levels of familiarity with the Münster cycling infrastructure. Participants were provided informed consent prior to the study and received monetary compensation for their participation.

3.5.2 Experimental Procedure and Measurement

The experiment followed a structured sequence using a mid-fidelity interactive prototype to facilitate functional interactions (McCurdy et al., 2006). While the routing data was pre-computed, the prototype featured automated state-transitions to provide immediate feedback to user inputs.

1. **Onboarding**: Participants completed consent forms and a background survey.
2. **Training Phase**: A practice task was provided using a separate origin-destination (OD) pair to mitigate learning effects.

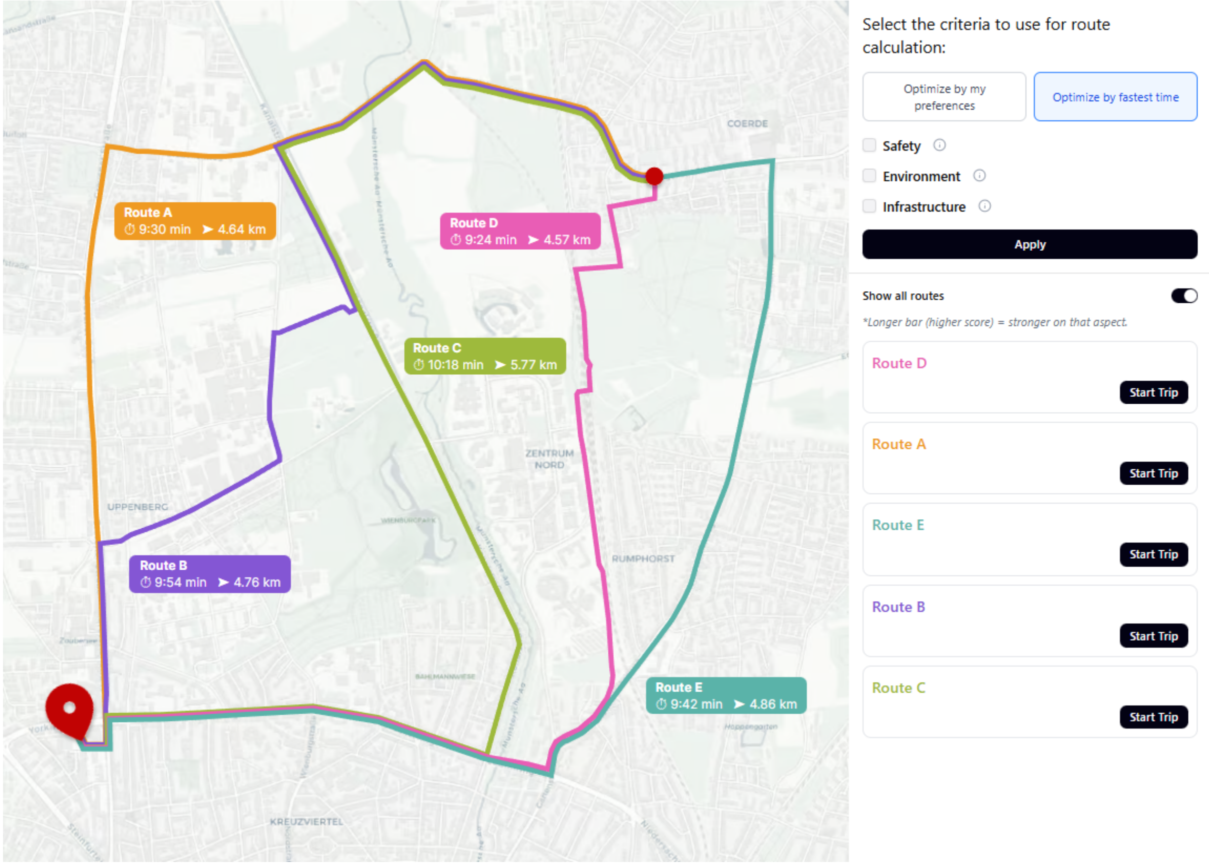


Figure 3.8: Dashboard overview using the checkboxes mechanism, optimized by fastest time, with Show all routes enabled.

3. **Experimental Blocks**: Participants completed two blocks of tasks (one per mechanism). For each mechanism, participants completed three types of tasks:

   - **Efficiency-Focused**: The participant was instructed to prioritize travel time, simulating a time-sensitive commute.
   - **Experience-Maximizing**: The participant was instructed to find the subjectively 'most pleasant' route, prioritizing experiential factors regardless of time.
   - **Constrained Trade-off**: A scenario where the route selected gives the highest quality experience but less than a minute longer than the fastest route, forcing the user to negotiate a personal threshold for acceptable delay.

   To control for potential confounding variables (Shadish, Cook, & Campbell, 2002), two levels of counterbalancing were implemented:

   - **Mechanism Order**: The order of mechanism exposure was alternated across participants (checkboxes-first or slider-first) to mitigate fatigue and learning effects.

- **OD Pair Order**: Six unique OD pairs were prepared to prevent participants from relying on route familiarity. Their presentation order was rotated to mitigate bias caused by exposure sequence.

Participants were free to adjust their preferences and regenerate route recommendations until they were satisfied with their choice. No time limits were imposed to ensure that data reflected natural decision-making.

4. **Post-Block Measurement**: Immediately after each block, participants completed the SUS, the NASA-TLX, custom Likert-scale items regarding trust and expressiveness, and brief open-ended questions about their experience with that specific mechanism.

5. **Comparative Measurement**: After completing both blocks, a final questionnaire in which the participants directly compared the mechanisms was administered.

6. **Debrief**: A semi-structured interview concluded the session to capture qualitative strategies.

The full list of questionnaire and interview items are detailed in Appendix C. The entire experiment took 40 minutes on average per participant.

3.6 Data Analysis Procedures

The analysis followed a mixed-methods strategy, distinguishing between the exploratory findings of the preliminary study and the confirmatory evaluation of the main experiment.

3.6.1 Preliminary Study: Analysis Procedures

Data from the preliminary user research were analyzed to inform the design of the main experimental prototype. Ordinal data from Likert ratings and ranking-based responses were analyzed using non-parametric statistical procedures (Sullivan & Artino, 2013). Paired comparisons between visualization conditions were conducted using Wilcoxon signed-rank tests, and effect sizes were computed using rank-biserial correlation to assess the magnitude and direction of observed differences. These analyses were used to identify relative strengths and weaknesses of different design options.

Open-ended responses were reviewed and summarized through an informal thematic grouping process to capture recurring comments and design-relevant observations. The analysis served to contextualize quantitative results and highlight potential interpretation issues or usability concerns raised by the respondents. Given the exploratory and design-oriented purpose of the preliminary study, this qualitative analysis was intentionally lightweight and exploratory.

Results of the preliminary analysis are summarized in Section 3.3 to motivate subsequent design decisions. More detailed statistical outputs and supporting analyses are provided in Appendix B. Findings from this stage were used to narrow the design space and guide the selection of visualization formats and interaction mechanisms implemented in the main experimental dashboard prototype.

3.6.2 Main Experiment: Analysis Overview

Quantitative Measures

Across all quantitative analyses, participant-level aggregation was used as the primary unit of analysis to satisfy independence assumptions and to ensure robustness to skewed distributions inherent in interaction and Likert-scale data (Carifio & Perla, 2008). Given the small sample size and non-normal distributions, all inferential analyses followed a non-parametric approach (Field, 2018).

Data from the main experiment were analyzed across three thematic blocks:

1. **System and Behavioral Performance**

   Four primary behavioral metrics, aggregated at the participant-level, were analyzed:

   - **Task completion time (TCT)** was measured in seconds from task initiation to final route selection. This metric was summarized using the median across the three tasks per mechanism to reduce the influence of occasional long exploratory tasks.
   - **Interaction effort** was captured through the number of explicit Apply clicks per task, summarized as the total across the three tasks per mechanism to capture cumulative interaction effort.
   - **All-routes exploration behavior** binarily described whether the Show all routes toggle was used in the tasks and summarized as the proportion of tasks in which this feature was enabled.
   - **Constraint compliance behavior** was measured as a binary indicator of whether the specified constraint was satisfied in the tasks. In the experimental design, exactly one constrained task was presented per mechanism for each participant.

2. **Usability and Workload**

   Usability and perceived workload were assessed using the SUS and NASA-TLX questionnaires, supplemented by custom Likert-scale items targeting mechanism-specific interaction qualities.

   - The **SUS** consists of ten items rated on five-point Likert scales. Item-level analyses of the SUS scores were conducted using raw Likert responses, while overall scores were computed following the standard SUS scoring procedure. Item scores were summed and multiplied by 2.5 to yield an overall SUS score ranging from 0 to 100 (Brooke, 1996).
   - The **NASA-TLX** questionnaire is comprised of six subscales, each rated on seven-point scales. Overall workload scores were computed as the unweighted mean of the six NASA-TLX subscales. Subscale-level analyses were conducted using the raw ratings (Hart & Staveland, 1988).
   - In addition to standardized questionnaires, participants completed a set of 7-point **custom Likert-scale items** designed to assess mechanism-specific aspects of interaction, including clarity of system behavior, expressiveness of control, communication of trade-offs, trust and decision confidence, and perceived usefulness in different routing contexts.

3. **Post-Interaction Perceptions**

   This block aimed to assess perceived speed, ease, clarity, intuitiveness, task-goal alignment, and adoption intentions.

   - The final questionnaire was designed to capture participants' subjective perceptions of the two mechanisms after completing the interaction tasks. The 7-point scale **custom Likert items** were phrased either to favor one mechanism explicitly (e.g. "The slider was easier to use than the checkboxes") or to assess preferences and willingness to use the mechanisms in practice.

Statistical Analysis Procedures

Quantitative data were processed in the R (Version 2024.12.1) statistical computing environment. Across all numeric data, descriptive statistics were computed at both the aggregated and item or subscale levels. Interpretation prioritized medians and interquartile ranges (IQRs) to reflect the ordinal structure of the data, but reported statistics also included the mean, standard deviation (SD), standard error (SE), 95% confidence interval (CI), median absolute deviation (MAD), and minimum and maximum values.

The responses of the questionnaire were evaluated using paired Wilcoxon signed-rank tests (Wilcoxon, 1945). This test was selected as it does not assume a normal distribution, making it appropriate for Likert-scale data and the observed distributions of interaction size (Sullivan & Artino, 2013). One-sample tests were used to evaluate the response patterns of individual items, and paired-sample tests were to quantify comparisons between mechanisms. To account for multiple comparisons, Holm's step-down procedure (Holm, 1979) was applied to adjust the p-values of the individual items. Statistical significance was then assessed using p-values at an alpha level of 0.05, while practical relevance and dominant directionality were quantified using rank-biserial correlation (r_{rb}) and median paired differences (Δ_{median}), computed as the median of within-participant differences. To complement these statistical tests, boxplots, paired slope plots, and difference plots were generated to assess distributional differences between mechanisms and illustrate heterogeneity across responses.

Supplementarily, learning effects were evaluated two ways. First, behavioral metrics were aggregated separately for the first block of tasks (T1–T3) and the second block of tasks (T4–T6) and compared within participants using paired Wilcoxon signed-rank tests. This analysis tested for systematic performance changes over time irrespective of the control method used. Second, to further control for task content, matched task pairs with identical instructions were compared across task positions: T4–T1 (efficiency-focused), T5–T2 (experience-maximizing), and T6–T3 (constrained trade-off). This allowed learning or familiarity effects to be assessed while holding task demands constant.

Qualitative Analysis and Triangulation

All interviews were transcribed and analyzed using manual inductive thematic analysis, following the approach by Braun and Clarke (2006). The coding process focused on identifying recurring explanatory patterns in user behavior, with particular attention to how participants articulated trade-offs, navigated uncertainty, and interpreted system feedback. The final codebook (Table 3.2) comprised five thematic categories, each encompassing multiple codes that captured distinct but related aspects of participant behavior and perception.

The final stage of the analysis involved within-stage triangulation to examine patterns of convergence and divergence across behavioral metrics, quantitative questionnaire responses, and qualitative data (Bekhet & Zauszniewski, 2012). Quantitative results identified significant differences in mechanism performance, whereas qualitative themes explained the underlying drivers of these patterns.

Table 3.2: Thematic structure of qualitative analysis.

Theme	**Description**
Decision Strategies and Exploration	How participants explored, compared, and iterated during route choice, including the strategies used to navigate trade-offs and integrate information across views
Mechanism Expressiveness	How interaction mechanisms enabled or constrained the articulation of preferences, including perceptions of control and granularity
Cognitive Effort and Ease	Participants' perceived mental workload, ease of use, and moments of confusion or clarity during interaction
Transparency and Trust	How participants understood system logic and developed confidence in route recommendations, including perceptions of clarity, transparency, and trust
Feature Salience, Constraints, and Trade-Offs	Which dashboard features participants found salient, how constraints were noticed or overlooked, and how trade-offs between efficiency and experiential factors were negotiated across contexts

3.7 Ethical Considerations

The study received ethics approval prior to data collection. All participants were informed of the study purpose, procedures, and their rights, including the right to withdraw. Data were anonymized and stored securely, and no personally identifying information was included in the analysis or reporting of results.

Ethics documents are attached in Appendix E

Chapter 4

Results

Quantitative analysis was performed in three thematic blocks – system and behavioral performance, usability and workload, and post-interaction perceptions – then triangulated with open-ended responses from questionnaires and interviews. As such, the flow of this section follows the same progression. Supplementary tables that support the information presented in this chapter are in Appendix D.

4.1 Behavioral Performance and Interaction Behavior

This section examines whether the two preference-adjustment mechanisms, checkboxes and slider, resulted in measurable differences in objective task performance. Each participant completed three routing tasks using each mechanism. Behavioral data logged include TCT, interaction effort based on Apply clicks, and all-routes exploration which was quantified by the use of the Show all routes toggle. In addition, the adherence of participants to task constraints was tracked.

4.1.1 Descriptive Behavioral Patterns

Task-level descriptive analyses (Table 4.1) and distributional plots (Figure 4.1) show substantial variability in TCT and interaction behavior across tasks, even within the same participant. Some tasks were completed rapidly with minimal interaction, while others involved longer durations and more extensive exploration. This variability suggests that TCT is influenced by exploratory decisions that are task-specific (e.g., experimenting with alternative routes or inspecting trade-offs) and not by participant-level performance.

Task-level performance is not statistically independent since multiple tasks were linked to a participant; hence, data per participant were aggregated into one summary value using the median to characterize exploration patterns. This ensures fair and

Table 4.1: Task performance metrics by mechanism

	TCT (seconds)				'Apply' Clicks			
Mechanism	**Median**	**IQR**	**Min**	**Max**	**Median**	**IQR**	**Min**	**Max**
Checkbox	34.0	27.75	10	226	1	1.75	1	11
Slider	38.5	29.25	9	299	1	2.00	1	6

accurate comparisons between different conditions in the study.

Participant-level behavioral metrics were summarized separately for the checkbox and slider mechanisms using medians and IQRs. To limit the influence of occasional long exploratory tasks, the median TCT was used to represent a typical task duration per participant. Apply clicks were summed across tasks to capture overall interaction effort per participant. *All-routes exploration* was summarized as the proportion of tasks in which all route options were shown. *Constraint compliance* behavior reflects whether the constraint was satisfied in the constrained task, which occurred exactly once per mechanism for each participant.

Descriptive summaries for both TCT and interaction effort are shown in Table 4.2. Supporting this, igures 4.1b and 4.1d depicts the overlap of these indicators across mechanisms, indicating comparable performance levels. Figures 4.1b and 4.1d also illustrate this. Wide IQRs across all metrics point to substantial differences in how each participant engaged with the dashboard.

Table 4.2: Participant-level task performance by mechanism

Mechanism	**TCT (seconds)**		**Apply Clicks**		**All-routes exploration (%)**	**Constraint compliance (%)**
	Median	**IQR**	**Median**	**IQR**		
Checkbox	34.5	24.5	5.5	4.00	24.4	88.5
Slider	39.5	22.5	6.0	3.75	29.5	88.5

4.1.2 Paired Comparison Between Interaction Mechanisms

Paired Wilcoxon signed-rank tests were conducted at the participant level to assess whether behavioral performance differed between interaction mechanisms. In addition to the test statistic (W) and p-values, rank-biserial correlation (r_{rb}) were reported as nonparametric effect sizes, and median paired differences (Δ_{median}) were computed to quantify the typical magnitude of difference between mechanisms. The Δ_{median} were calculated by subtracting checkbox performance from slider performance for each participant and summarizing these differences using the median. The results are summarized in Table 4.3.

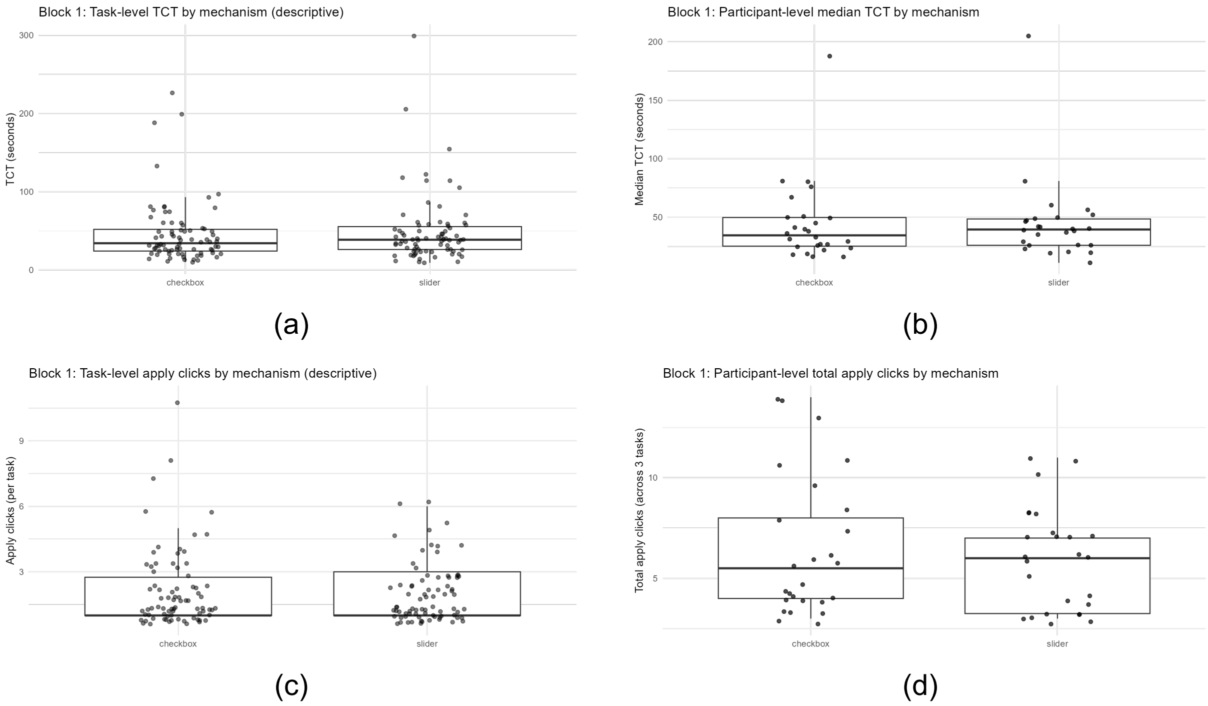


Figure 4.1: Distribution plots of interaction behavior. Panels show (a) TCT across all tasks, (b) median TCT per participant, (c) Apply clicks across all tasks, and (d) median Apply clicks per participant.

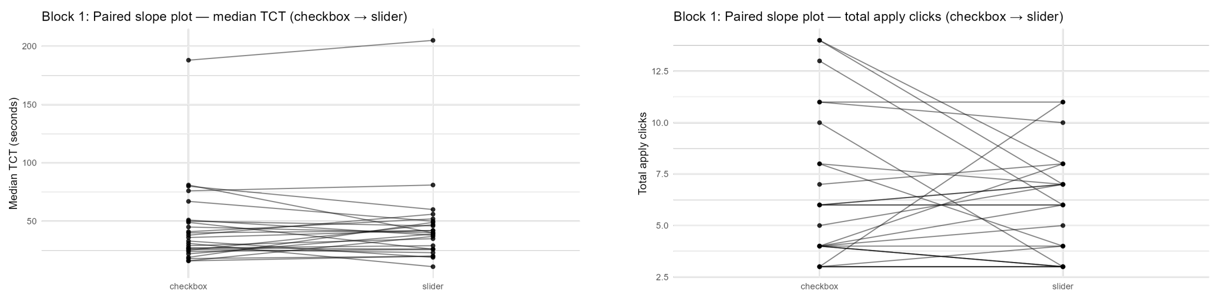
Table 4.3: Statistical test results across evaluated metrics

Metric	W	p	r_{rb}	Δ_{median}
TCT	190	0.722	0.08	2
Apply clicks	83	0.638	-0.13	0
Show all routes	14.5	0.462	0.38	0
Constraint compliance	10.5	1.000	0.00	0

Across all behavioral metrics, no statistically significant differences were observed between mechanisms. Furthermore, effect sizes were small and median paired differences were negligible that no clear pattern could be found.

Participant-level paired slope plots provide complementary insights. Figure 4.2a shows that TCT across the mechanisms, although largely clustered, have no consistent directional trend across participants. It further reveals that the non-significant result is not driven by outliers or opposing subgroups, but by small and inconsistent within-participant changes.

Unlike TCT, Figure 4.2b depicts more dispersed and heterogeneous trajectories for interaction effort. Here, the slope plot is particularly informative as it demonstrates that the non-significant aggregate result reflects substantial individual variability rather than similar performance across conditions.



(a) (b)

Figure 4.2: Task behavior paired slope plots. The panels show participant-level trends of (a) median TCT and (b) total Apply clicks.

Overall, Figure 4.2 highlight inconsistent individual trends - some participants were more efficient with one mechanism, whereas others showed the opposite pattern. This suggests that differences between mechanisms vary across participants, leaving negligible effects at the aggregate level.

4.1.3 Learning Effects based on Task Order

To examine potential learning or order effects, participant-level performance in the first half of the block (tasks T1–T3) was compared with performance in the second half (tasks T4–T6), regardless of interaction mechanism (Table 4.4. A paired comparison revealed a statistically significant reduction in median TCT ($p = 0.036$) in the second half of the block, indicating a modest learning effect. Although most participants showed no change, some participants made use of the Show all routes feature less in the second half of the block, and an r_{rb} value of -1 indicates that no participant increased their use of this feature. No corresponding significant change was observed for Apply clicks.

Because this comparison is independent of mechanism identity, it suggests that participants became faster over time due to increased familiarity with the task or interface,

Table 4.4: Paired comparison of position effects to task behavior.

Metric	W	p	r_{rb}	Δ_{median}	Δ_{IQR}
TCT median	92.5	0.036	-0.47	-5	19.75
Total Apply clicks	128	0.183	0.35	0.5	1
Show all routes (%)	0	0.036	-1.00	0	0

rather than because of the interaction mechanism itself. Furthermore, there is reduced reliance on global route exploration as participants became more familiar with the task.

Supporting this, task pairs with identical instructions were compared to control for task-content differences: T4–T1 (efficiency), T5–T2 (experience-maximizing), and T6–T3 (constrained trade-off). Median differences in TCT (ΔTCT_{median}) and interaction behavior (Δint) were computed for each pair (Table 4.5).

Table 4.5: Matched task-pair TCT differences.

Pair	$\Delta TCT_{\text{median}}$	Δint
Efficiency	-4.0	29.25
Experience-maximizing	-5.5	23.00
Constrained trade-off	1.5	32.25

Across all three instruction types, median TCT differences consistently favored the second-position tasks. Since each comparison involves identical task instructions, this pattern is unlikely due to task-specific difficulty. This supports the interpretation of a general learning or familiarity effect.

4.2 Usability and Cognitive Workload

4.2.1 Usability and Workload Outcomes (SUS & NASA-TLX)

Since no significant order effects were observed for overall SUS or NASA-TLX paired differences (all $p > .05$), results are reported irrespective of presentation order.

Overall usability, as measured by the SUS differed between the two mechanisms (Table 4.6). Median scores were higher for the checkboxes than for the slider. A paired Wilcoxon signed-rank test indicated that this difference was statistically significant ($W = 53$, $p = 0.009$), with a large effect size ($r_{rb} = -0.62$), suggesting higher perceived usability for the checkboxes mechanism.

On the other hand, overall perceived workload, assessed using the NASA-TLX, did not differ significantly between mechanisms (Table 4.7). Median scores were comparable between the checkboxes and slider, and the paired Wilcoxon test indicated no

Table 4.6: Overall SUS descriptive statistics

Mechanism	Median	IQR
Checkboxes	85.00	16.88
Slider	77.50	19.38

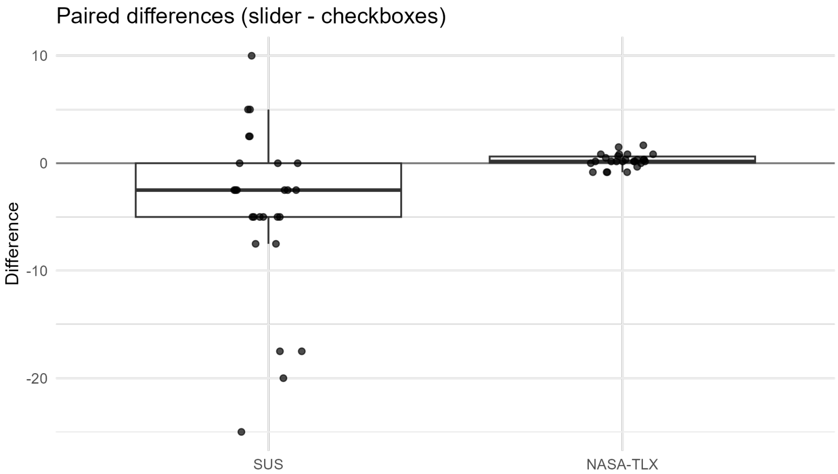


Figure 4.3: Paired differences of overall SUS and NASA-TLX scores.

statistically significant difference (W = 214.5, p = 0.067). This implies the absence of a systematic workload difference between mechanisms.

Table 4.7: Overall NASA-TLX descriptive statistics

Mechanism	Median	IQR
Checkboxes	2.08	1.38
Slider	2.17	1.33

Figure 4.3 shows the distribution of paired differences (slider − checkboxes) for overall usability and perceived workload. For SUS, most paired differences lie below zero, indicating higher usability scores for the checkboxes mechanism compared to the slider. This visual pattern is consistent with the paired Wilcoxon signed-rank test, which revealed a statistically significant difference in SUS scores between conditions. In contrast, paired differences for NASA-TLX are tightly clustered around zero, indicating that perceived workload was largely comparable across interaction mechanisms. This aligns with the non-significant result of the paired Wilcoxon test for overall NASA-TLX scores.

Together, the box plots of paired differences complement the statistical analysis by illustrating both the direction and magnitude of within-participant changes, clarifying that the significant usability effect observed for SUS is not mirrored by differences in perceived workload.

To better understand which aspects of usability contributed to the difference in overall scores, item-level SUS responses were examined analyzed (Table 4.8).

Table 4.8: Paired tests of item-level SUS.

Item	W	p_{raw}	p_{holm}
(sus_1) frequency of use	54	0.212	1.000
(sus_2) complexity	85.5	0.037	0.293
(sus_3) ease of use	39.5	1.000	1.000
(sus_4) need for support	15	0.374	1.000
(sus_5) function integration	25	0.824	1.000
(sus_6) inconsistency	94	0.007	0.072
(sus_7) learnability	32.5	0.594	1.000
(sus_8) awkwardness of use	21	0.714	1.000
(sus_9) confidence in use	5	0.023	0.211
(sus_10) training effort	46	0.236	1.000

At the uncorrected level, there were nominal differences observed on items related to perceived complexity (sus_2), inconsistency (sus_6), and confidence in use (sus_9); however, none remained statistically significant after Holm adjustment. This suggests that lower usability ratings for the slider mechanism were generally small to moderate in magnitude, varied across participants and not driven by a single usability dimension; instead, the low ratings are distributed across multiple items.

Wilcoxon signed-rank tests on the NASA-TLX subscale scores revealed that the differences in overall workload pattern were driven primarily by mental demand (Table 4.9). The slider (median = 3, IQR = 3) received statistically significant higher scores with a large effect size in terms of mental demand compared to checkboxes (median = 2; IQR = 2).

Table 4.9: Paired tests of NASA-TLX subscale ratings.

Subscale	W	p_{raw}	r_{rb}	p_{holm}
effort	73	0.199	0.390	0.99
frustration	68	0.329	0.295	1.00
mental demand	170.5	0.002	0.795	0.01
performance	89.5	0.547	0.170	1.00
physical demand	15	0.930	0.071	1.00
temporal demand	46.5	0.447	-0.225	1.00

Figure 4.4 presents the distribution of paired differences (slider − checkboxes) for the NASA-TLX subscales. While most subscales show differences clustered around zero, indicating comparable perceived workload across interaction mechanisms, the

mental demand subscale exhibits a noticeable shift away from zero. This visual pattern is consistent with the paired Wilcoxon signed-rank test results, which identified a statistically significant difference for mental demand, whereas no significant differences were observed for the remaining subscales.

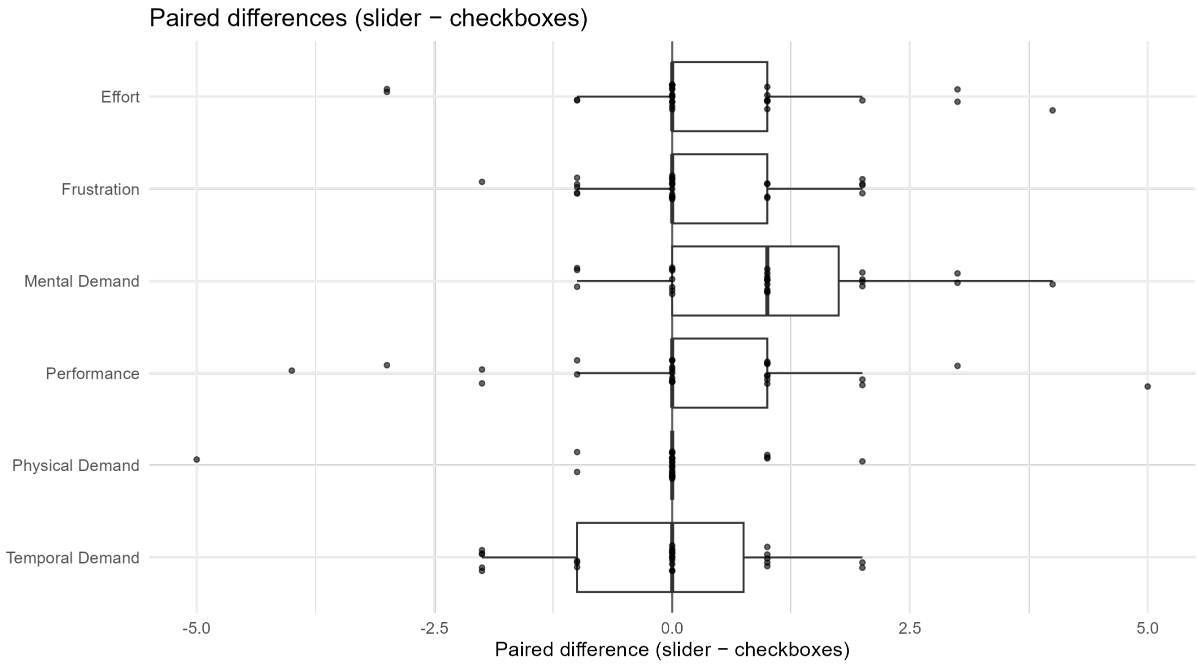


Figure 4.4: Paired differences of subscale-level NASA-TLX scores.

4.2.2 Mechanism-Specific Perceptions (Custom Items)

Participants completed a set of custom Likert-scale items designed to assess clarity of system behavior, expressiveness of control, communication of trade-offs, trust and decision confidence, and perceived usefulness across contexts. Negatively worded items were reverse-scored so that higher values consistently indicate more favorable evaluations.

After Holm correction for multiple comparisons, none of the individual custom Likert items showed statistically significant paired differences between mechanisms (all $p_{holm} > .05$). The results reported below therefore describe descriptive patterns and participant-level trends.

Items related to clarity of system behavior and trade-off communication tended to show higher median ratings under the checkboxes mechanism. Participants generally reported clearer understanding of how preference adjustments affected route rankings and greater ease in interpreting differences between recommended routes.

By contrast, items related to expressiveness of control showed a more mixed pattern. While the slider mechanism was often perceived as offering greater expressive flexibility, this was accompanied by higher perceived difficulty in setting preferences as intended, suggesting a trade-off between expressiveness and interaction ease.

Items assessing trust in route accuracy and confidence in route choice also tended to favor the checkbox mechanism, indicating greater perceived reliability and decisional confidence. Perceived usefulness for familiar everyday routing followed a similar pattern, whereas usefulness for unfamiliar contexts showed greater variability across participants.

Overall, the custom Likert items suggest that the checkbox mechanism supports clearer mental models, greater trust, and higher confidence, whereas the slider mechanism affords expressiveness at the cost of increased interaction difficulty.

4.3 Post-Interaction Perceptions

This section focuses on participants' perceptions of the two mechanisms using custom 7-point Likert-scale questionnaire items, where higher values indicate stronger agreement (1 = strongly disagree, 7 = strongly agree). Analyses focus on descriptive distributions, deviations from a neutral midpoint ($\mu = 4$), and the magnitude of observed effects. One-sample Wilcoxon signed-rank tests were conducted against the μ (Table 4.10). Supporting this, Figure 4.5 shows the agreement distribution of the comparative ratings against μ.

Table 4.10: Wilcoxon test results of custom Likert items.

Item	**Median**	W	p	$r_{\mathbf{rb}}$
checkboxes allowed faster decisions	6.0	222	0.002	0.66
slider was easier to use	2.0	96.5	0.120	0.31
checkboxes were more confusing	2.0	13.5	0.000	0.80
slider felt more intuitive	4.5	165.5	0.204	0.27
slider better supported task goals	6.0	216	0.016	0.49
intention to use checkboxes	5.0	192	0.097	0.34
intention to use slider	6.0	183.5	0.161	0.29
slider preferred over checkboxes	5.5	189	0.262	0.23

Participants' perceptions of interaction speed and ease differed across preference-adjustment mechanisms. Responses to *checkboxes allowed faster decisions than the slider* showed a median rating of 6, which was significantly above the neutral midpoint of the scale (Wilcoxon one-sample test, $p = 0.002$). This difference was associated with a large practical effect size ($r_{rb} = 0.66$). This indicates a consistent perception that checkboxes-based preference adjustment enabled faster interaction. In contrast, perceptions of ease showed a weaker pattern. Ratings for the statement that the *slider*

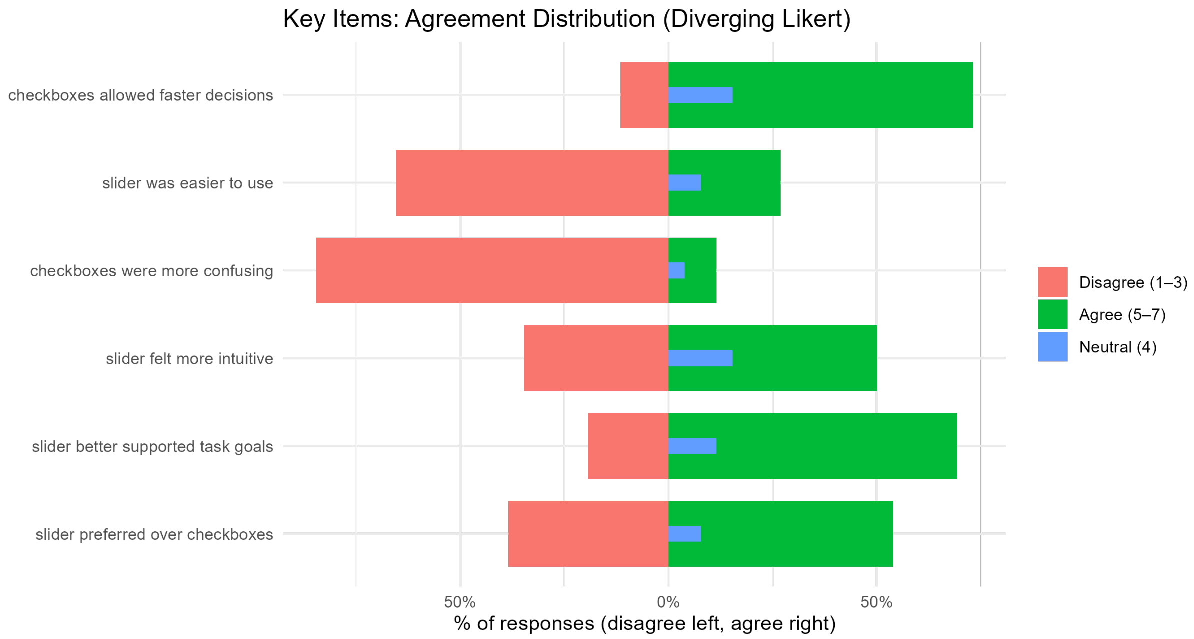


Figure 4.5: Agreement distributions of custom Likert-item comparative ratings.

was easier to use than the checkboxes did not differ significantly from the neutral midpoint. These findings suggest that, while checkboxes were clearly perceived as faster for decision-making, sliders were not consistently perceived as easier to use.

Perceptions of intuitiveness and confusion further differentiated the two mechanisms. Participants strongly disagreed with the statement that the *checkboxes were more confusing to use than the slider* (median = 2, $p < 0.001$). This was accompanied by a large effect size ($r_{rb} = 0.80$), indicating that the checkboxes mechanism was generally perceived as clear and easy to understand. On the other hand, ratings for the statement that the *slider felt more intuitive than the checkboxes* were not statistically significant. This suggests that although some participants found the slider more intuitive, this perception was not consistent to establish a clear group-level advantage over checkboxes.

Participants' evaluations of how well each mechanism supported their task goals revealed a clearer distinction. Ratings for the statement that the *slider better supported task goals* showed a significantly positive response (median = 6, $p = 0.016$) associated with a medium effect size ($r_{rb} = 0.49$), indicating that participants perceived sliders to have a meaningful advantage for task-related preference expression. This result suggests that the slider mechanism affords greater preference granularity, enabling users to express graded trade-offs between competing criteria. This perceived advantage emerges despite the absence of consistent differences in ease or intuitiveness.

Adoption intentions were assessed using parallel items measuring participants' willingness to use a checkboxes-based or a slider-based version of the dashboard in practice. Ratings for both mechanisms were generally positive, with medians above the neutral midpoint. Despite differences in perceived speed, clarity, and preference granularity, participants did not express a clear overall preference for adopting one mechanism over the other. This is evidenced by a paired Wilcoxon signed-rank test comparing intention-to-use ratings for the two mechanisms, which was revealed to have no statistical significance ($p = 1.00$). Additionally, ratings for overall preference for the slider were moderately positive but did not differ significantly from neutrality, reinforcing the absence of a dominant mechanism in terms of adoption intent.

In sum, post-interaction perception results show no dominant overall preference for either interaction mechanism. Participants attributed different strengths to each mechanism, with checkboxes linked to speed and sliders more often associated with task-goal alignment.

4.4 Triangulation and Integration of Results

4.4.1 Integrated Triangulated Findings

Table 4.11 summarizes participant-level qualitative mentions associated with each interaction mechanism. Counts indicate the number of participants who mentioned each theme at least once in the open-ended survey responses or during interviews. Participants may contribute to multiple categories.

Table 4.11: Frequency of qualitative themes by interaction mechanism

Theme	**Checkboxes**	**Slider**
described as fast / quick / straightforward	16	–
described as clear / easy to understand	2	–
described as decisive (include / exclude)	2	–
described as fine-grained / precise / flexible	–	12
mentions of experimentation or incremental adjustment	–	12
mentions of increased cognitive effort	–	5
context-based preference (familiar vs unfamiliar routes)	7	7
context-based preference (time pressure vs exploration)	7	7

Quantitative usability results indicated higher perceived usability for checkboxes, converging with interview data pattern. The checkboxes mechanism was often described as fast, quick, straightforward, or simple (16 participants). A smaller number additionally characterized it as clear or easy to understand (2 participants) or as supporting decisive selection through inclusion or exclusion of criteria (2 participants). These qualitative descriptions align with behavioral and questionnaire-based findings indicating lower interaction overhead and higher perceived usability for checkboxes.

While the checkboxes mechanism shows a usability advantage, triangulation reveals an important divergence when considering preference articulation and task-goal alignment. Quantitative evidence indicated that slider-based interaction was rated as better supporting participants' task goals, even though it did not receive higher overall usability scores. Qualitative findings clarify this divergence as 12 participants described slider-based interaction to be fine-grained, precise, flexible, or flexible to adjust preferences little by little. Participants frequently reported using sliders to incrementally modify preferences and observe corresponding changes in route recommendations. These descriptions indicate that the slider was associated with greater perceived control over preference articulation, even when usability ratings favored the checkboxes.

Quantitative workload results showed no statistically significant difference in overall NASA-TLX scores between interaction mechanisms. However, subscale-level analysis indicated higher mental demand associated with the slider mechanism. Qualitative data help reconcile this finding as 5 participants explicitly reported thinking more, paying more attention, or needing additional time when adjusting preferences using sliders. This suggests that sliders prompt users to engage more deeply with trade-offs, but this does not translate into greater overall perceived workload.

Qualitative interview data provide descriptive context on why no dominant preference or adoption intention emerges. Preferences were differentiated based on route familiarity, contrasting familiar and unfamiliar routing scenarios, as mentioned by 7 participants. A separate group of 7 participants differentiated preferences based on time pressure or planning style, contrasting quick decision-making with more exploratory or careful planning. Additionally, the checkboxes mechanism was more frequently associated with situations requiring speed or decisiveness, whereas the slider mechanism was more frequently associated with exploratory planning or unfamiliar routing contexts. These contextual distinctions appeared consistently across participants and correspond with the balanced adoption intentions observed in quantitative results. This pattern indicates heterogeneity in user needs and strategies.

Overall, the triangulated findings show that differences between mechanisms cannot be explained by performance or usability measures alone. While checkboxes-based interaction tended to support faster and more decisive behavior, slider-based interaction facilitated finer-grained preference articulation and deeper engagement with trade-offs without increasing overall perceived workload. Participants' evaluations and adoption intentions were highly context-dependent, indicating that each mechanism supports distinct reasoning strategies rather than a single superior interaction approach.

4.4.2 Additional Qualitative Findings

In addition to the triangulated findings above, there were several recurring observations during post-task interviews and task execution that were not directly aligned with the quantitative outcomes but reflect experienced interaction characteristics of the system.

Participants tended to trust in route recommendations more when routes were simultaneously visualized on the map alongside numerical scores or ranks. There were 4 participants who explicitly noted that seeing the route geometry helped them relate abstract scores to familiar spatial context and increased their confidence in the recommendations.

Issues with visual discrimination were also reported. According to 6 participants, difficulty was faced when distinguishing between routes and associated metrics when similar color schemes were used across the map and coordinated visual components. These comments occurred despite the presence of linked highlighting and were described as occasional and not persistent.

There were several mentions of friction when doing the tasks. Three participants expressed a desire for route recommendations to update automatically as preferences were adjusted, rather than requiring an explicit confirmation action before changes are applied. These comments suggest occasional usability issues during exploration but were not formally measured.

Moreover, participants frequently relied on the OE score when comparing routes (10 participants). Explicit mentions of using this aggregate score as a benchmark for comparing alternatives arose consistently.

Participants also favored the tooltip functionality that provided brief descriptions of experiential factors upon hover. Frequent use of this feature was observed during the main experiment, and several participants commended this component during interviews.

Finally, participants raised observations regarding the transparency of score computation across interaction mechanisms. Three participants reported that the computation underlying checkboxes was unclear, whereas the slider was described easier to understand. Participants noted that the explicit display of weights summing to 100 in the slider mechanism helped clarify how individual factors contributed to the OE score.

Chapter 5

Discussion

This discussion interprets the findings of the main experiment by integrating user behavior, subjective feedback, and qualitative interviews to understand how interaction design shapes reasoning in spatial decision-support contexts. The findings did not identify a superior interaction technique, but these point to how different preference-adjustment mechanisms support different modes of reasoning about trade-offs between efficiency and experience in cycling route planning.

5.1 Behavioral Patterns Across Mechanisms

A core finding of this study is that, at the aggregate level, there is no significant difference between the checkboxes and the slider across behavioral measures such as TCT, interaction effort, and constraint-respected behavior.

The participants acknowledged individual preferences and performance advantages of the mechanisms, but the related quantitative trends resulted in small effect sizes and inconsistency across the sample; hence, this pattern should not be interpreted as inconclusive – rather, it reflects the exploratory nature of the tasks and the individual strategies employed when reasoning about spatial trade-offs, more so than the interaction mechanism itself. This resonates with prior design research, arguing that interaction variations do not fundamentally alter the information available for decision-making and that user reasoning strategies and task characteristics dominate measurable performance outcomes (Farzand et al., 2024; Friedl et al., 2021; Mosca, Ottley, & Chang, 2021).

These outcomes underscore that preference-adjustment mechanisms should be tailored to empower users to experiment, backtrack, and switch strategies. As per Young and Kitchin (2020), there is no single optimal way to cater to a general audience in multi-criteria geospatial dashboards – they should support flexible workflows that promote pivoting and learning.

Learning effects observed across task positions further support this interpretation. TCTs decreased in later tasks regardless of the mechanism, indicating that increased familiarity with the task structure played a more pivotal role than the specific preference-adjustment mechanism.

Taken together, these findings suggest that the negligible objective behavioral differences with the preference-adjustment mechanisms are meaningful. Instead of improving performance efficiency, these tools primary influence how users reason about and engage with trade-offs.

5.2 Interaction Mechanisms and Trade-off Reasoning

While behavioral performance outcomes were broadly similar, qualitative and triangulated findings indicate that the preference-adjustment mechanisms shape users' reasoning about trade-offs primarily by structuring how trade-offs are explored and articulated. As such, the checkboxes and slider mechanisms functioned not merely as input controls, but as cognitive scaffolds supporting distinct reasoning strategies that influenced how users engaged with efficiency and experiential factors during route planning. This aligns with prior research showing that interactivity in trade-off diagrams and systems shapes how users explore competing criteria (Oprean et al., 2019) and guide decision strategies (Ferreira et al., 2026), supporting the view that weighting mechanisms act as cognitive scaffolds.

The checkboxes supported a decisive reasoning mode, in which users applied clear inclusion or exclusion thresholds to experiential attributes to arrive at a satisfactory route. This allowed a simple and swift elimination process, emphasizing efficiency and clarity over nuanced weighting of factors. Consequently, this discrete mechanism facilitated higher perceived usability ratings by allowing users to commit to key factors and compare route options on a narrowed criterion.

In contrast, the continuous nature of the slider encouraged a more exploratory and deliberative reasoning mode, characterized by gradual adjustment, experimentation, and explicit fine-tuning of competing experiential attributes. This suggests that users are willing to accept increased cognitive effort when it results in greater transparency and a clearer understanding of how experiential factors shape route outcomes. This indicates that mental demand is not inherently negative; rather, it becomes valuable when it contributes to meaningful insight. For designers, the challenge is therefore not to eliminate cognitive load entirely, but to calibrate it such that it provides sufficient explanatory depth to support informed decision-making without overwhelming users, especially in time-sensitive planning situations. This mode was particularly relevant in unfamiliar or exploratory planning scenarios.

These findings respond to Research Question (RQ) 1 by showing that preference-adjustment mechanisms not only affect task efficiency but also fundamentally shape how users think. Rather than determining which route is selected, the interaction design influences the reasoning strategy users adopt: discrete preference specification encourages fast, threshold-based comparisons, while continuous adjustment promotes gradual negotiation of competing experiential factors. From an HCI perspective, this demonstrates that interface mechanisms actively structure cognitive engagement, aligning with theories of externalized cognition (Dimara et al., 2020). This distinction is particularly salient in a geospatial context, as users must integrate diverse data – spatial layout, route geometry, and experiential attributes – into a coherent decision.

5.3 Trade-Off Between Efficiency and Deliberation

Usability and workload findings elucidate the relationship between reasoning effort and preference-adjustment mechanism. The slider yielded lower overall usability and higher perceived mental demand, despite no substantial difference in overall workload the two preference-adjustment mechanisms. Item-level patterns and custom Likert responses suggest that these differences were mostly distributed across multiple dimensions rather than driven by a single component.

The checkboxes reduced cognitive effort with a simplified preference specification, facilitating rapid and confident decisions. In contrast, the higher mental demand with the slider reflects the cognitive effort involved in articulating and weighting nuanced preferences. Participants frequently reported that they are thinking more when using the slider, which aligns with their exploratory adjustment behavior. Zhou et al. (2024) frame this not as a deficiency, but as a trade-off between efficiency and expressiveness, where the cognitive cost of the slider reflects the expressive power granted to the user. Dimara et al. (2020) further support this by arguing that desirable discomfort or cognitive friction can be a feature that facilitates more nuanced reasoning.

There is a clear efficiency–expressiveness trade-off between mechanisms that supports RQ2. The checkboxes mechanism supports efficient preference specification and decision-making while the slider mechanism offered greater expressive control at the cost of increased mental demand. These differences in perceived effort and usability are closely tied to the type of reasoning encouraged by each mechanism.

These findings highlight an important distinction for decision-support systems: lower cognitive effort and higher usability do not necessarily equate to better support for complex decision-making. In tasks where trade-offs are central, interaction designs that encourage thoughtful exploration or deliberation may be desirable in some contexts, even if they feel more demanding. Rather than identifying a single optimal mechanism, the results point to a fundamental trade-off between efficiency-oriented and deliberation-oriented approaches.

5.4 Context, Trust, and Experience Communication

The absence of a dominant preference or adoption intention across mechanisms underscores the context-dependent nature of preference-adjustment mechanisms. Participants consistently framed their evaluations in relation to route familiarity, time pressure, and purpose of the trip. The checkboxes mechanism was often described as suitable for familiar or time-constrained situations, whereas the slider mechanism was favored for unfamiliar routes or exploratory planning scenarios. This aligns with the research by Skarlatidou et al. (2011), where perceived utility in Web geographic information system (GIS) interfaces was found to be highly dependent on the prior spatial knowledge of the user and the specific task at hand.

Qualitative evidence also emphasizes the role of effectively translating abstract experiential qualities into clear information in shaping trust and understanding. Participants relied heavily on synthesized representations, such as the OE score, to orient themselves before engaging in deeper comparison. Additionally, tooltips, which provided the contextual explanation of experiential metrics, were essential transparency features that fundamentally increased the trust in the system. As Wanner et al. (2022) suggests, when users can see the rationale behind a recommendation, their perceived competence of the system increases.

Differences in perceived clarity of score computation further highlight the importance of transparency. The explicit weighting structure of the slider, with visible proportions summing to 100, made causal relationships between preferences and outcomes more legible for some participants. Conversely, while checkbox interaction felt simpler, unclear mapping between selections and score computation sometimes limited users' understanding of how preferences influenced results. These findings suggest that trust in spatial decision-support tools emerges not only from interaction simplicity, but from the clarity with which trade-offs are communicated. This aligns with the concept of steerability and causal relationship in co-adaptive guidance, where trust is built through seeing the consequence of interactions with an interface (Sperrle et al., 2021).

With respect to RQ3, the findings suggest that understanding, trust, and perceived usefulness in cycling-related spatial decision support systems emerge not from any single interface component, but from the coordinated integration of preference-adjustment mechanisms and transparent visual representations. The reliance on overview displays before engaging in detailed comparisons indicates that cyclists' trust moves progressively from global orientation to local evaluation. The absence of a universally preferred mechanism indicates that cyclists' needs shift across contexts, shaped by familiarity, planning goals, and confidence, reinforcing the importance of flexible interface designs over fixed recommendation approaches.

5.5 Limitations and Implications for Interpretation

The following constraints clarify the conditions under which the observed patterns in this study are relevant.

First, the study evaluated a single prototype with specific encodings of experiential factors and preference-adjustment mechanisms. While the prototype reflects common patterns in route-planning dashboards, alternative layouts, interaction metaphors, or weighting schemes may elicit different perceptions and reasoning strategies. Therefore, these results explain how the checkboxes and slider mechanisms functioned within this specific design context and are not definitive for all possible implementations.

Second, the evaluation was based on short, task-based interactions rather than real-world use. Since the participants engaged in exploratory routing tasks without experiencing downstream consequences of actual navigation, the observed reasoning modes and preference patterns primarily reflect initial sensemaking rather than habitual interaction behavior. Differences in cognitive effort or preference formation may evolve with extended use.

Third, the sample size (n = 26) detected medium to large effects, and smaller perceptual differences may not have reached statistical significance. In this context, the absence of significant group-level effects should not be viewed as proof that the mechanisms are identical; instead, they should be interpreted alongside effect sizes, individual-level variability, and convergent qualitative patterns.

Finally, learning effects observed across task positions indicate that familiarity with the interface and task structure influenced performance independently of interaction mechanism. This suggests that some efficiency-related outcomes may reflect task acclimation effects rather than interaction design alone, although acclimation was not explicitly modeled or controlled for. Accordingly, differences observed in early interactions may not necessarily persist as users become more familiar with the dashboard over time.

These limitations imply that the findings of this study should be interpreted as contextual and explanatory, rather than as predictive claims about long-term performance or universal user preferences.

5.6 Summary of Key Findings

The study suggests that preference-adjustment mechanisms not only facilitate data entry but also mediate how users engage with spatial trade-offs by supporting different reasoning modes. Three core insights emerged in the synthesis of these findings.

First, effective communication of trade-offs in cycling route planning depends heavily on how preference-adjustment mechanisms, checkboxes and slider, externalize user reasoning than on optimizing for behavioral efficiency. This depicts that the mechanisms serve as cognitive scaffolds for complex decision-making. Second, the checkboxes and the slider represent a fundamental trade-off – checkboxes favor usability and low cognitive effort, while sliders offer greater expressiveness and control at the cost of higher mental demand. This suggests that the optimality of the mechanism is defined by the depth of precision required by the task. Third, user understanding and trust are shaped by the coordination of visual components and the transparency of the underlying scoring logic. Furthermore, the perceived usefulness of these tools is highly dependent on context such as route familiarity and planning purpose.

Overall, the results indicate that no single preference-adjustment mechanism is universally optimal. Instead, these mechanisms act as mediators that support different reasoning strategies across varying contexts. These insights form the basis for the design implications in the following section, which translate the observed patterns into principles for orienting interactive geospatial trade-off DSS.

Chapter 6

Design Implications

This study contributes a set of empirically grounded design guidelines for interactive geospatial decision-support dashboards. The guidelines are particularly relevant for dashboards intended for diverse user groups with varying levels of spatial familiarity, as well as for different cycling route-planning contexts, such as commuting and exploratory planning.

Although derived from a cycling route-planning context, the following guidelines target a broader class of interactive geospatial dashboards designed to communicate trade-offs between efficiency and experiential factors. Their adaptability extends as well to other systems that share similar characteristics such as those involving multi-criteria spatial decisions, requiring users to balance competing objectives, and considering subjective or experiential factors. That is because these guidelines capture universal interaction patterns and design tensions common to multi-criteria spatial tasks – such as trade-offs between expressiveness and usability, and transparency and cognitive effort (Dimara et al., 2020; Vincent et al., 2019; Wanner et al., 2022). Some comparable interactive multi-criteria spatial decision systems – where users dynamically explore trade-offs among heterogeneous spatial criteria to guide planning and policy decisions – are renewable energy siting (Hashunao et al., 2024; Shao et al., 2020), disaster risk mapping (Tang et al., 2018), and urban land suitability analysis (Setfane & Ouazzani Touhami, 2025; Ullah & Mansourian, 2016). Nonetheless, rather than universal solutions, these guidelines focus on balancing design tensions to support adaptable and informed design decisions.

Collectively, these design guidelines (Tables 6.1 and 6.2) constitute a primary contribution of this research, bridging empirical findings and practical design decisions for scalable geospatial decision-support systems.

Table 6.1: Design guidelines for interactive route-planning and trade-off–oriented geospatial dashboards.

Code	Guideline	Design Intent
G1	Support multiple reasoning modes within the same dashboard	Enable both decisive and exploratory sensemaking by accommodating diverse cognitive strategies
G2	Align interaction mechanisms with planning context and intent	Match interaction styles to users' situational constraints and goals
G3	Make preference-to-outcome relationships transparent	Improve understanding, trust, and confidence by clarifying how preference adjustments influence outcomes
G4	Provide layered information to support comparison	Support progressive sensemaking by enabling both overview and detailed spatial inspection
G5	Design for learning and familiarity effects	Treat early interaction as a learning phase that supports improved performance over time

Table 6.2: Empirical basis and application of the design guidelines.

Code	Application Context	Design Tension	Empirical Basis
G1	Spatial planning tasks involving multi-criteria trade-offs, particularly where users must balance quantifiable metrics with subjective or context-dependent considerations	Supporting multiple modes may increase interface complexity and cognitive load	Distinct participant preferences for checkboxes-based versus slider-based mechanism, reflecting decisive versus exploratory reasoning strategies
G2	Dashboards intended for heterogeneous contexts (e.g., familiar vs. unfamiliar routes, time-constrained vs. exploratory planning)	Requires adaptive interfaces or explicit mode-switching functionality	Checkboxes-based mechanism was preferred in contexts of spatial and route familiarity or under time pressure, whereas slider-based mechanism supported planning in unfamiliar or exploratory routing scenarios
G3	Multi-criteria scoring, ranking, or weighting systems	Greater transparency may increase cognitive effort by exposing underlying decision logic, which some users may prefer not to engage with	Improved trust and clarity reported when weighting structures and outcome effects were visible, particularly in the slider-based mechanism
G4	Dashboards comparing multiple spatial alternatives, where each alternative is evaluated across multiple contributing factors	Poorly designed aggregation risks oversimplification or misinterpretation	Participants relied on aggregated experience scores for orientation before inspecting route geometry and spatial detail
G5	First-time or infrequent use of decision-support dashboards	Additional onboarding or guidance may slow expert users	Performance improvements across successive tasks suggest learning effects during initial interaction

Chapter 7

Conclusions and Future Research

7.1 Synthesis

This thesis examined how different interaction mechanisms influence user behavior, understanding, and decision-making in an interactive geospatial dashboard for cycling route planning. Rather than evaluating the accuracy of routes and the associated descriptive metrics, the study focused on how users interpret and reason about efficiency–experiential trade-offs when adjusting preferences through alternative interaction mechanisms.

Across the conducted tasks, the results show that interaction mechanisms had negligible effects on objective performance, such as TCT or interaction effort, regardless of the mechanism used. This outcome should not be interpreted as a design defect of the prototype as it indicates that performance is not influenced by the form of preference-adjustment mechanism, but by the nature of the tasks and the individual strategies employed.

More substantial differences emerged regarding how users balanced trade-offs, perceived control, and interpreted the consequences of their adjustments. Participants used interaction mechanisms not merely to input preferences, but as cognitive scaffolds that facilitated distinct reasoning strategies in balancing efficiency and experiential considerations. These patterns suggest that the checkboxes leaned towards efficiency-oriented reasoning as it supported quicker, more decisive interactions. The slider, on the other hand, aligned with a more deliberation-oriented sensemaking, encouraging a more reflective exploration between competing factors.

The overarching implication of these findings is that, in short, exploratory cycling route planning tasks, the interaction mechanisms have limited influence on the user's performance outcomes. Instead, they partake primarily in shaping users' sensemaking processes, particularly in how trade-offs are understood, justified, and trusted.

7.2 Research Contributions

This thesis contributes to existing work in geospatial decision support and HCI by reinforcing, contextualizing, and operationalizing established concepts through empirical evaluation and design synthesis.

From an empirical perspective, the study provides further evidence that different interaction mechanisms can lead to comparable performance outcomes while supporting distinct reasoning strategies. This finding aligns with prior research suggesting that interaction design often influences how decisions are made rather than how fast they are completed.

Conceptually, the thesis situates theories of sensemaking and cognitive scaffolding within the context of geospatial route planning dashboards. The study strengthens the perspective that input controls structure users' decision processes.

Methodologically, the work demonstrates a mixed-methods evaluation approach that combines controlled tasks, usability and subjective workload measures, as well as qualitative feedback.

Finally, this thesis makes a design-oriented contribution by translating empirical findings into practical design guidelines for multi-criteria geospatial decision-support dashboards. Although grounded in cycling route planning, these guidelines are formulated to support broader mobility and spatial decision-support systems – such as those that negotiate trade-offs in MCDM frameworks.

7.3 Directions for Future Work

This thesis contends that interaction mechanisms primarily influence how users interpret and reason about trade-offs, rather than how efficiently they complete tasks. This central finding points to several directions for future research and iterative design development.

From a design perspective, dashboard iterations should prioritize improving the legibility of trade-offs. Examples include features that collate efficiency and experiential metrics in a single, integrated view, such as summary tables or compact comparison panels. Interaction feedback loops could also be strengthened by allowing route recommendations to update without explicit confirmation steps as preferences are adjusted, reducing friction during exploration. Careful attention to visual design – such as colorblind safe palettes and the application of contrasting color schemes across different information layers – would further support cognitive clarity, especially with overlapping datasets. Rather than seeking a single optimal interaction mechanism, future designs could explore alternative forms of preference-setting that balance expressiveness and cognitive simplicity. For example, allowing users to assign coarse ordinal weights (e.g., high, medium, and lowlow) to route factors may offer an interpretable middle ground between binary selections and continuous sliders, while still supporting comparison across multiple criteria.

From an evaluation perspective, longer-term or repeated use of similar systems could be examined to investigate learning effects and changes in interaction preferences. Extending evaluation to contexts with more constrained cycling infrastructure would also be valuable, as such environments may amplify trade-off tensions, thereby magnifying the influence of interaction design choices in user reasoning. Furthermore, in-situ navigation contexts could help assess how interaction design functions under different cognitive constraints.

Future research may also explore how the findings and design principles in this study apply to spatial decision-support tools beyond the context of cycling route planning.

Across these recommended research trajectories, this thesis underscores the importance of interaction design in supporting users' understanding of trade-offs in multi-criteria geospatial DSS.

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Appendix A

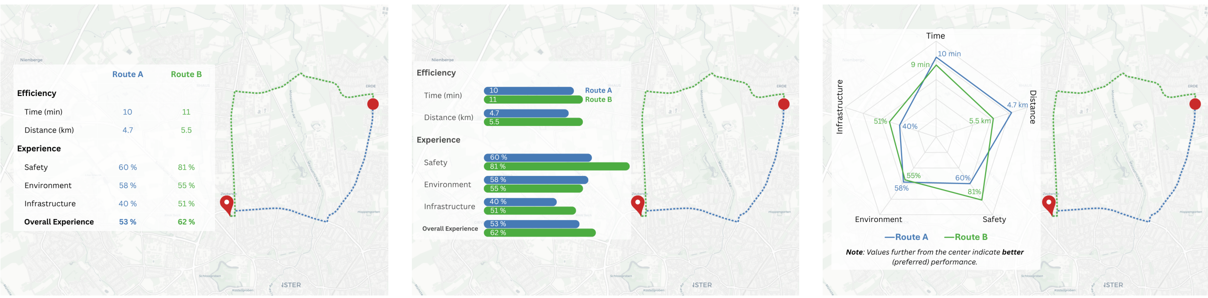
Preliminary Study Survey Instrument

This appendix documents the full survey instrument used in the preliminary online study. The survey was implemented using Google Forms and consisted of multiple conceptual blocks, each corresponding to a specific stage of the study design. Across blocks, identical question sets were repeated verbatim for different visualization and interaction conditions; only the presented stimuli varied.

The complete survey instrument is provided in Table A.1. Within the table, items are grouped into six blocks reflecting the survey flow experienced by a single respondent: (1) respondent information, (2) visualization block, (3) visualization block reflection, (4) interaction controls block, (5) interaction controls reflection, and (6) final reflection.

The survey began with respondent information, capturing demographic characteristics, cycling experience, and details of a frequently made urban cycling trip.

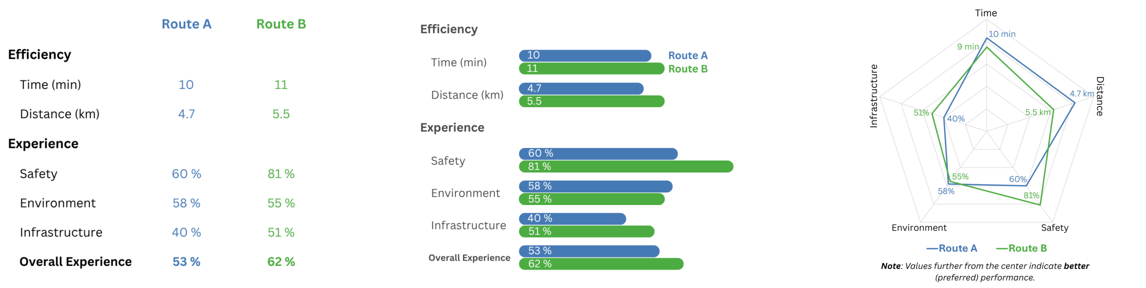
The visualization block then presented participants with route comparison dashboards using three different visualization formats—table, bar charts, and diagram—shown both with and without spatial context. For each visualization condition, participants answered the same set of evaluative questions assessing perceived efficiency, experiential clarity, trade-offs, and decision confidence. Figure A.1 and Figure A.2 illustrate the visualization stimuli with and without a map, respectively.



(a) table with map (b) bar charts with map (c) diagram with map

Figure A.1: Visualization block stimuli with spatial context.

Participants then completed a visualization block reflection, in which they compared

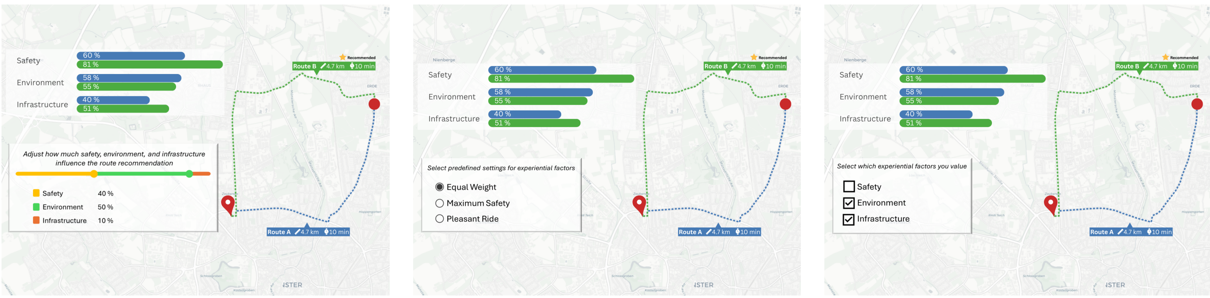


(a) table without map (b) bar charts without map (c) diagram without map

Figure A.2: Visualization block stimuli without spatial context.

visualization formats across conditions and reflected on the role of spatial context in interpreting route information.

In the interaction controls block, participants were shown static representations of three preference-adjustment mechanisms—slider, preset categories, and checkboxes—and answered an identical set of questions for each control type. These questions assessed usability, perceived control, and usefulness for expressing experiential preferences. The interaction control stimuli are shown in Figure A.3,



(a) slider (b) preset categories (c) spider diagram

Figure A.3: Interaction control static stimuli.

This block was followed by an interaction controls reflection question set, where participants compared control types across conditions.

Finally, the survey concluded with a final reflection block, which assessed clarity of terminology, perceived usefulness and trustworthiness of the dashboard concept, understanding of trade-offs, and overall applicability to participants' daily cycling. Open-ended questions in this block invited participants to articulate interpretations, concerns, and suggestions for improvement.

To reduce potential order effects within the constraints of Google Forms, two versions of the survey were deployed (Form A and Form B). Both versions contained the same set of visualization and interaction conditions, but differed in presentation order. In Form A, visualization conditions with spatial context were presented before non-spatial conditions, whereas Form B reversed this order. Additionally, the initial visualization format was rotated across versions. Each participant completed only one survey version. This design ensured that all participants were exposed to the full set of experimental conditions while mitigating systematic bias due to ordering or fatigue effects.

Table A.1: Preliminary study survey items. The left column lists the questionnaire items, while the right column describes the corresponding response options or rating scales.

Respondent Information	
Age range	$<$18; 18–24; 25–34; 35–44; 45–54; 55+
Gender	Woman; Man; Non-binary; Prefer not to say
How many years have you been cycling regularly in urban areas?	0–1; 2–3; 4–5; 6+
On average, how often do you cycle in urban areas?	5–7 days/week; 3–4 days/week; 1–2 days/week; Never
People value different things when cycling. Which of these best describes you for your usual rides?	Fast Commuter; Comfort Seeker; Calm & Pleasant Rider; Infrastructure Prioritizer; Other
Please choose one regular trip you make most often by bicycle.	Work/School; Grocery/Market errand; Church/Weekly appointment; Child drop-off/pick-up; Other
How often do you make this trip in a typical week?	5–7 days; 3–4 days; 1–2 days; 0 (rarely)
About how long is this trip (one way)?	$<$3 km; 3–5 km; 5–10 km; 10–15 km; $>$15 km; Not sure
Which of these conditions usually apply to this trip?	Heavy motor traffic; Frequent interruptions (e.g. traffic lights, complex intersections); Hilly/steep gradients; Adverse weather; Poor/rough surface; High noise/air pollution; Carrying cargo/passengers; Cycling at night; Other
For this trip, how rushed do you usually feel?	1 = Not at all rushed … 7 = Very rushed
How familiar are you with your usual route for this trip?	1 = Not familiar … 7 = Very familiar
How familiar are you with alternative routes you could take for the same trip?	1 = Not familiar … 7 = Very familiar
Where do you usually cycle? (Please name the city and country.)	Open-ended response
Visualization Block	
I could tell which route was faster.	1 = Strongly Disagree … 7 = Strongly Agree
I could tell which route would give a better cycling experience.	1 = Strongly Disagree … 7 = Strongly Agree

It is easy to see how the two routes differ across the indicators.	1 = Strongly Disagree … 7 = Strongly Agree
This display clearly shows a trade-off between efficiency and experience.	1 = Strongly Disagree … 7 = Strongly Agree
Based on this view, I could confidently choose one of the routes.	1 = Strongly Disagree … 7 = Strongly Agree
If you had to pick, which route would you choose?	Route A; Route B; Not sure
I would trust information shown in this type of display.	1 = Strongly Disagree … 7 = Strongly Agree
What did you like about this display?	Open-ended response
What was confusing or unclear about this display?	Open-ended response
Visualization Block Reflection	
Which type of display felt clearest overall to you?	Table; Bars; Diagram; Not sure
Which display style would you prefer in a real cycling app? (Rank 1–3)	Table; Bars; Diagram
The presence of the map helped interpret efficiency information.	1 = Strongly Disagree … 7 = Strongly Agree
The presence of the map helped interpret experiential information.	1 = Strongly Disagree … 7 = Strongly Agree
When comparing routes, how important was seeing a map?	1 = Not important at all … 7 = Very important
When a map was shown, what information did you use?	Turns/complexity; Length; Busy roads; Surroundings; Route differences; Overlap/divergence; Did not help; Other
Which was more helpful when assessing routes?	Route paths; Metrics; Both equally; Not sure
Overall, was it easier to understand information with a map?	With a map; Without a map; No difference
Other ways route comparison could be shown more clearly?	Open-ended response
Interaction Controls Block	
What happens when you adjust this control?	Changes experiential weighting; Changes time/distance; Changes map colors only; Not sure
I find this control easy to use.	1 = Strongly Disagree … 7 = Strongly Agree

This control makes me feel in control of the recommendation.	1 = Strongly Disagree … 7 = Strongly Agree
This control helps adjust what matters most to me.	1 = Strongly Disagree … 7 = Strongly Agree
What could make this control clearer or more useful?	Open-ended response
Interaction Controls Reflection	
Which control type felt clearest overall?	Slider; Preset Categories; Checkboxes; No preference
Which control type would you prefer in a real app? (Rank 1–3)	Slider; Preset Categories; Checkboxes
Which control type offers the most flexibility?	Slider; Preset Categories; Checkboxes; Not sure
How helpful would predefined rider profiles be?	1 = Not helpful at all … 7 = Very helpful
For your usual commute, which control suits you best?	Slider; Preset Categories; Checkboxes; Not sure
Why did you select that control option?	Open-ended response
Other controls that could be clearer or more useful?	Open-ended response
Final Reflection	
The meaning of the term *Efficiency* was clear to me.	1 = Strongly Disagree … 7 = Strongly Agree
The meaning of the term *Experience* was clear to me.	1 = Strongly Disagree … 7 = Strongly Agree
The meaning of Time, Distance, Safety, Environment, and Infrastructure was clear.	1 = Strongly Disagree … 7 = Strongly Agree
Would you rename any of these indicators?	Open-ended response
This dashboard would help me plan or adjust my routes.	1 = Strongly Disagree … 7 = Strongly Agree
I would trust recommendations from this dashboard.	1 = Strongly Disagree … 7 = Strongly Agree
I would use this dashboard in a real cycling app.	1 = Strongly Disagree … 7 = Strongly Agree
How would you use this dashboard in daily cycling?	Open-ended response
The idea of showing efficiency–experience trade-offs is useful.	1 = Strongly Disagree … 7 = Strongly Agree
I understood how the dashboard communicates these trade-offs.	1 = Strongly Disagree … 7 = Strongly Agree

Based on the image, what is the trade-off with the safer route?	Time/distance increased; Time/distance decreased; About the same; Not sure
This dashboard would help me make more informed decisions.	1 = Strongly Disagree … 7 = Strongly Agree
Was anything confusing or missing?	Open-ended response
How useful would this dashboard be for you personally?	1 = Not useful at all … 7 = Extremely useful
Please provide a short rationale for your answer.	Open-ended response
If you could improve or personalize this dashboard, what would you change?	Open-ended response

Appendix B

Supplementary Results from Preliminary Study

This appendix reports the detailed results and interpretation of the preliminary survey. The analysis focused on comparing alternative visualization formats, the presence of a map, and preference-adjustment mechanisms. The findings were used to narrow down dashboard elements prior to the main experiment.

B.1 Quantitative Findings

Pairwise Wilcoxon signed-rank tests (Table B.1) revealed that the diagram-based visualization performed significantly worse than both bar charts and tables across clarity, confidence, and trust, with large effect sizes. Differences between bar charts and tables were generally non-significant. This pattern was consistent across map and no-map conditions.

Figure B.1 shows the distribution of participant rankings for visualization types. The table and bar charts were most frequently ranked first or second, whereas the diagram visualization was predominantly ranked last.

Paired comparisons between map and no-map conditions (Table B.2) showed no significant differences for clarity across visualization types. Map presence moderately increased confidence in diagram visualizations. Furthermore, a moderate increase in trust was observed for table-based displays when paired with a map. These findings suggest that the map primarily supports trust and verification rather than improving metric interpretability.

As illustrated in Figure B.2, checkboxes were most frequently ranked as the preferred control mechanism, followed by the slider. The preset-based mechanism was often ranked last, indicating lower user preference.

All control-related scales demonstrated acceptable to excellent internal consistency

Table B.1: Pairwise Wilcoxon signed-rank tests across visualization formats.

family	**var 1**	**var 2**	**W**	**p**	$r_{\textbf{rb}}$
clarity_map	table	bar chart	158	0.127	-0.27
clarity_map	table	diagram	450.5	0.000	0.69
clarity_map	bar chart	diagram	481	0.000	0.79
clarity_nomap	table	bar chart	148.5	0.334	-0.17
clarity_nomap	table	diagram	485.5	0.000	0.81
clarity_nomap	bar chart	diagram	514.5	0.000	0.81
confidence_map	table	bar chart	90	0.859	0.03
confidence_map	table	diagram	335.5	0.000	0.71
confidence_map	bar chart	diagram	437.5	0.000	0.74
confidence_nomap	table	bar chart	69	0.979	0.00
confidence_nomap	table	diagram	417	0.000	0.76
confidence_nomap	bar chart	diagram	401.5	0.000	0.79
trust_map	table	bar chart	112.5	0.790	0.05
trust_map	table	diagram	328	0.000	0.68
trust_map	bar chart	diagram	332	0.000	0.70
trust_nomap	table	bar chart	78	0.302	0.18
trust_nomap	table	diagram	336	0.000	0.71
trust_nomap	bar chart	diagram	453.5	0.000	0.71

Table B.2: Wilcoxon test results (map vs. no-map) by construct and visualization type

Construct	**Visualization**	**W**	**p**	$r_{\textbf{rb}}$
clarity	table	169	0.638	0.08
clarity	bars	167.5	0.186	0.23
clarity	diagram	228.5	0.180	0.23
confidence	table	130.5	0.149	0.25
confidence	bars	124	0.086	0.30
confidence	diagram	156.5	0.009	0.45
trust	table	177	0.007	0.47
trust	bars	63.5	0.051	0.34
trust	diagram	146.5	0.098	0.29

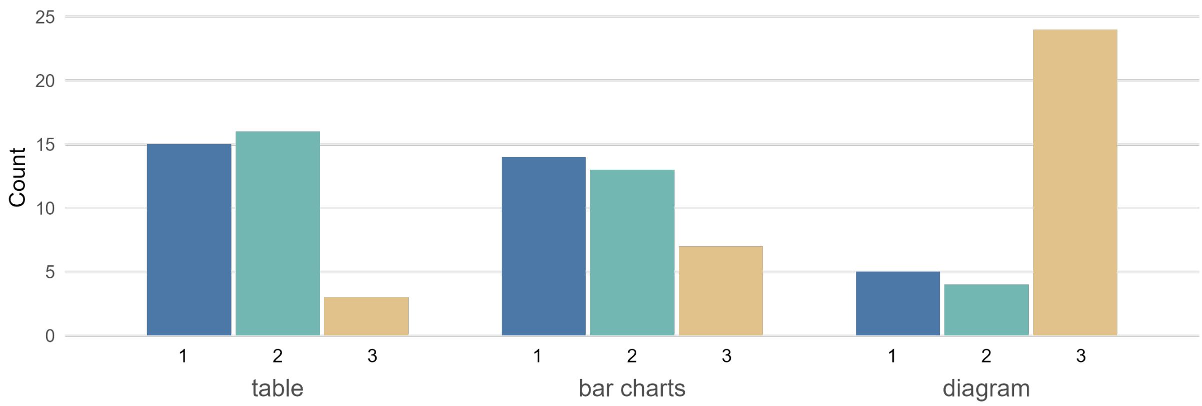


Figure B.1: Ranking distribution of visualization types.

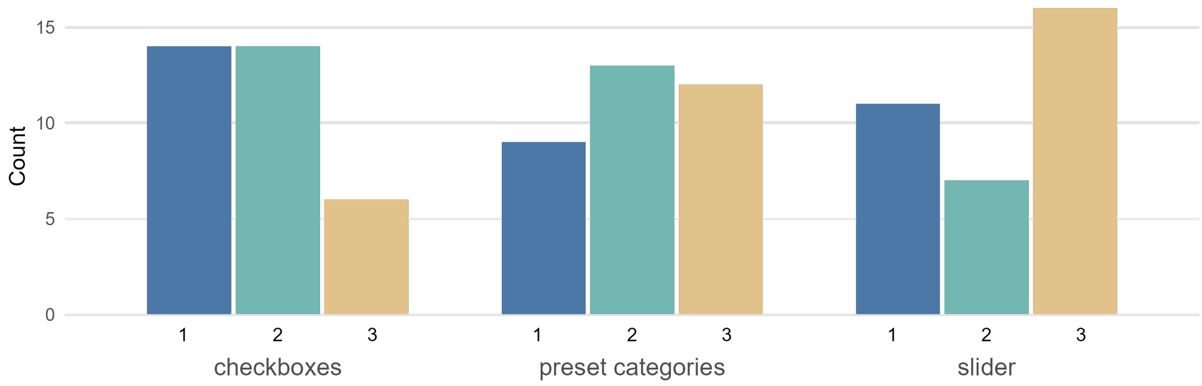


Figure B.2: Ranking distribution of control mechanisms.

(α ≈ 0.84–0.95), supporting their use in subsequent analyses (Table B.3).

Table B.3: Reliability of control mechanism scales (Cronbach's α).

Scale	α	α_{std}
checkboxes	0.95	0.95
preset categories	0.85	0.84
slider	0.93	0.93

B.2 Qualitative Triangulation of Quantitative Findings

Open-ended responses were examined to triangulate the quantitative results and to support the design narrowing decisions.

The qualitative responses closely mirrored the quantitative performance differences between visualization types. Bar charts were consistently described as intuitive and easy to interpret. It was found to enable quick identification of metric differences between routes, especially when combined with color cues and a map. The table was valued for their structure and transparency and were often perceived as trustworthy, especially when paired with a map; However, it was also associated with information overload and unclear indicator definitions. The diagram-based visualization was predominantly described as complex and cognitively demanding, with many participants reporting difficulty interpreting the radial format, especially in the absence of a map. These observations align with the significantly lower clarity, confidence, and trust ratings observed for the diagram.

The respondents generally preferred the inclusion of a map, primarily as a means of contextual grounding and verification. The map helped users relate the quantitative indicators with the spatial characteristics of the routes, increasing confidence in their interpretations. Without a map, respondents reported uncertainty about route complexity and context. However, some noted that combining a map with dense visualizations could increase visual clutter, suggesting a need for careful prioritization of displayed information. This pattern is consistent with quantitative results, which showed a selective influence of map presence on perceived trust.

The responses also clarified the trade-offs between different control mechanisms. The slider was associated with flexibility and a stronger sense of control but was also perceived as more cognitively demanding. The checkboxes mechanism was described as simple and quick but confusion arose about how multiple selections were weighted. Preset-based controls were frequently described as restrictive or unclear, explaining their lower preference rankings.

Efficiency indicators were generally well understood, while experiential indicators were found more ambiguous. Participants suggested adding short definitions or visual cues to improve clarity. Overall, the dashboard concept was perceived as useful and trustworthy, especially for unfamiliar routes or trip planning, but less necessary for well-known daily commutes.

B.3 Design Narrowing Decisions

The findings from the preliminary survey were used to narrow down the dashboard elements prior to the main experiment. Quantitative comparisons showed that the table and bar charts consistently outperformed the diagram-based visualization across clarity, confidence, and trust. Consequently, the diagram-based view was excluded from the prototype used in the main experiment. Although no evidence emerged for a meaningful distinction between the table and bar charts, the table view was found less engaging for visual comparison and requires more cognitive effort to interpret trade-offs; hence, bar charts were selected as the primary means of communicating experiential route attributes. Additionally, map presence contributed positively to perceived trust, supporting its inclusion as a core component of the dashboard. Finally, preference-adjustment mechanisms were refined based on both ranking data and reliability analysis. Checkboxes and sliders were retained due to higher preference and interpretability, whereas preset-based controls were excluded as they were often described as confusing or overly restrictive. Overall, these findings informed the final configuration of the dashboard evaluated in the main experiment.

Appendix C

Main Experiment Materials and Questionnaires

This appendix presents the materials (dashboard prototype, questionnaires, and interview items) used in the main experiment.

The dashboard prototype testing materials are available for inspection at the following link: `https://egg-cheer-08933852.figma.site/`. The link provides access to the six OD pairs used in the main experimental tasks. The prototype also includes predefined test sequences, which were selected by the experimenter to organize these OD pairs into a fixed order and ensure uninterrupted testing. Participants did not interact with the sequence selection interface.

The full questionnaire is documented in Table C.1, which consolidates all items across the different stages of the study.

After completing each interaction block, participants answered the same post-block questionnaire. As the study followed a within-subjects design, each participant completed this questionnaire twice—once after using each preference-adjustment mechanism. The corresponding post-block items included SUS, NASA-TLX, and custom items, which are specified in the Post-Block Questionnaire section of Table C.1.

Table C.1: Main experiment questionnaires. The left column lists questionnaire items, while the right column describes the corresponding response options or rating scales.

Participant Background	
Age	$<$18; 18–24; 25–34; 35–44; 45–54; 55+
Gender	Woman; Man; Non-binary; Prefer not to say
Highest education level completed	High school or equivalent; Vocational/Technical or some college; Bachelor's degree; Master's degree; Doctoral degree; Other
Profession / field of study	Open-ended response

How many years have you been cycling regularly in urban areas?	0–1; 2–3; 4–5; 6+
On average, how often do you cycle in urban areas?	5–7 days/week; 3–4 days/week; 1–2 days/week; Rarely
Primary purpose of cycling (select all that apply)	Commuting; Recreation; Errands; Sport/Training
General comfort and skill level in using digital tools	1 = Novice … 5 = Expert
How often do you use digital navigation apps (e.g., Google Maps, Komoot)?	Multiple times per day; Several times per week; Once per week; A few times per month; Rarely; Never
Have you used tools that allow adjusting multiple preferences or weighting factors?	Yes, frequently; Yes, occasionally; Not sure / not familiar; No
Familiarity with Münster's cycling infrastructure	1 = Not familiar … 5 = Very familiar
Post-Block Questionnaire (per Interaction Mechanism)	
How mentally demanding was the task? (Mental demand)	1 = Very low … 7 = Very high
How physically demanding was the task? (Physical demand)	1 = Very low … 7 = Very high
How hurried or rushed did you feel? (Temporal demand)	1 = Very low … 7 = Very high
How successful were you in performing the task? (Performance)	1 = Perfect … 7 = Failure
How hard did you have to work to accomplish your level of performance? (Effort)	1 = Very low … 7 = Very high
How frustrated, irritated, or stressed did you feel? (Frustration)	1 = Very low … 7 = Very high
I think that I would like to use this system frequently.	0 = Strongly disagree … 4 = Strongly agree
I found the system unnecessarily complex.	0 = Strongly disagree … 4 = Strongly agree (reverse scored)
I thought the system was easy to use.	0 = Strongly disagree … 4 = Strongly agree
I would imagine that most people would learn to use this system very quickly.	0 = Strongly disagree … 4 = Strongly agree
I understood how my adjustments affected which routes were shown.	1 = Strongly disagree … 7 = Strongly agree
This control method gave me the level of control I needed over safety, environment, and infrastructure.	1 = Strongly disagree … 7 = Strongly agree

The control method clearly communicated the trade-offs and consequences of prioritizing certain route factors.	1 = Strongly disagree … 7 = Strongly agree
How were the recommended routes chosen? (select all that apply)	Shortest travel time; Highest overall experience score; Randomly selected; Not sure
What did you like most about this control method?	Open-ended response
What did you dislike most about this control method?	Open-ended response
If you could improve one thing about this control method, what would it be?	Open-ended response
Final Mechanism Comparison Questionnaire	
The Slider was easier to use than the Checkboxes.	1 = Strongly disagree … 7 = Strongly agree
The Checkboxes allowed me to decide faster than the Slider.	1 = Strongly disagree … 7 = Strongly agree
The Slider felt more intuitive to me than the Checkboxes.	1 = Strongly disagree … 7 = Strongly agree
Overall, I preferred using the Slider rather than the Checkboxes.	1 = Strongly disagree … 7 = Strongly agree
I would use a cycling app that uses a Slider for adjusting route preferences.	1 = Strongly disagree … 7 = Strongly agree
I would use a cycling app that uses Checkboxes for adjusting route preferences.	1 = Strongly disagree … 7 = Strongly agree

Upon completion of both interaction blocks, participants completed a short wrap-up questionnaire capturing overall impressions, preferences, and comparative judgments between the two mechanisms. These final comparison items are documented in the Final Mechanism Comparison Questionnaire section of Table C.1.

Participants then took part in a brief semi-structured debriefing interview. The interview guide used to support these discussions, including the primary questions and follow-up prompts together with their analytical purpose, is provided in Table C.2 for reference.

Table C.2: Main experiment interview guide. The left column lists interview questions together with their follow-up prompts, while the right column describes their analytical purpose or rationale.

Question	Purpose / Rationale
Q1. Can you describe your strategy for minimizing effort or time when using the *[interaction mechanism]*? **Follow-up:** Was there any feature or step that forced you to pause or slow down the most?	Probes mental effort, decision strategies, and perceived interaction friction.
Q2. Can you give a specific example of a preference (e.g., balancing conflicting metrics) that you could express well with one mechanism but not the other?	Evaluates the mechanism's ability to support preference articulation and expressiveness.
Q3. When using either mechanism, did you rely more on deliberate preference-setting or on trial-and-error? **Follow-up:** How did the map and bar chart visualizations support or hinder the strategy you chose?	Examines how interaction mechanisms and visual feedback jointly shape user strategies.
Q4. When comparing the recommended routes, how did you decide when a compromise was acceptable or "too much"? **Follow-up:** Which metrics or visual elements were most important in making that decision?	Probes participants' decision heuristics and criteria for evaluating trade-offs.
Q5. Did the recommended routes feel accurate and reliable? **Follow-up:** Which dashboard features helped you feel confident or trust the suggested routes?	Captures factors influencing trust and perceived system competence.
Q6. How easy or difficult was it to connect the routes shown on the map with the bars in the chart? Did the highlights help you understand which bar belonged to which route? **Follow-up:** Did you ever feel unsure whether the map and chart were showing the same information?	Evaluates the clarity and coherence of coordinated multiple views and identifies visualization issues.
Q7. Would a dashboard like this be useful for your regular rides? Why or why not? Would it be useful for planning unfamiliar rides? **Follow-up:** When comparing the two mechanisms, did you find either more useful for familiar routes or for unfamiliar ones?	Assesses contextual suitability and situational preferences for interaction mechanisms.

Appendix D

Main Experiment Supplementary Tables

D.1 Objective and Subjective Measures.

Tables D.1 and D.2 provides the full descriptive and inferential statistics for behavioral performance metrics reported in the main text (Table 4.2). For TCT and Apply clicks, values are reported as per-participant medians with IQRs, together with minimum and maximum observed values, to account for skewed distributions commonly observed in interaction and task-performance data. Percentages are aggregated at the participant–task level. All metrics are reported separately for the checkbox and slider mechanisms.

Table D.1: Objective interaction metrics — TCT.

Mechanism	n	Mean	SD	Median	IQR	Min–Max
Checkboxes	26	44.4	35.1	34.5	24.5	16–188
Slider	26	44.6	36.1	39.5	22.5	11–205

Table D.2: Objective interaction metrics — Apply clicks.

Mechanism	n	Mean	SD	Median	IQR	Min–Max
Checkboxes	26	6.5	3.6	5.5	4.0	3–14
Slider	26	5.9	2.5	6.0	3.75	3–11

Item-level descriptive statistics for SUS (Table D.3) and NASA-TLX (Table D.4) are provided here to support the aggregate usability and workload comparisons discussed in Section 4.2.1. Additionally, Table D.5 summarizes the statistics that assess mechanism-specific aspects of interaction probed in Section 4.2.2. These tables allow inspection of which specific items contributed to observed differences between mechanisms.

Table D.3: Item-level SUS responses for checkboxes and slider,

Item	**Checkboxes**		**Slider**		W	p_{raw}	p_{holm}
	Median	**IQR**	**Median**	**IQR**			
(sus_1) frequency of use	4	1	4	1	54	0.212	1.000
(sus_2) complexity	1	1	2	2	85.5	0.037	0.293
(sus_3) ease of use	4	1	4	1	39.5	1.000	1.000
(sus_4) need for support	1	0	1	0.75	15	0.374	1.000
(sus_5) function integration	5	1	4.5	1	25	0.824	1.000
(sus_6) inconsistency	1	1	2	1	94	0.007	0.072
(sus_7) learnability	4	1	4	0.75	32.5	0.594	1.000
(sus_8) awkwardness of use	2	2	2	1.75	21	0.714	1.000
(sus_9) confidence in use	4.5	1	4	1	5	0.023	0.211
(sus_10) training effort	1	1	1	1	46	0.236	1.000

Table D.4: Subscale-level NASA-TLX responses for checkboxes and slider

Subscale	**Checkbox**		**Slider**		W	p_{raw}	r_{rb}	p_{holm}
	Median	**IQR**	**Median**	**IQR**				
effort	2	2.5	3	2	73	0.199	0.390	0.99
frustration	1	1	2	1	68	0.329	0.295	1.00
mental demand	2	2	3	3	170.5	0.002	0.795	0.01
performance	2	3.5	2	2	89.5	0.547	0.170	1.00
physical demand	1	1	1	1	15	0.930	0.071	1.00
temporal demand	2	2	2	1.75	46.5	0.447	-0.225	1.00

Table D.6 reports the detailed descriptive and inferential results for the final questionnaire assessing perceived preference, intuitiveness, and adoption intent, referenced in Section 4.3.

D.2 Block-Wise Order Effects

To evaluate potential learning or sequence effects across the study session, block-wise comparisons were conducted between Block 1 and Block 2 for TCT and interaction effort (Apply clicks). Because participants assigned to each block formed independent groups, Wilcoxon rank-sum tests were used.

Table D.5: Custom item responses for checkboxes and slider.

Item	Checkboxes		Slider		W	p_{raw}	p_{holm}
	Median	IQR	Median	IQR			
clarity of ranking logic	7	1	6	1.75	31	0.162	1.000
clarity of route difference	2	2	2	1	46	0.255	1.000
expressed control level	6	1.75	6	2	65.5	0.170	1.000
difficulty setting preferences	2.5	2	2	2.75	136	0.250	1.000
trade-off clarity	5.5	2	5	1.75	68.5	1.000	1.000
trust in route choice	6	1.5	6	1	15	0.209	1.000
trust in route accuracy	2	1.75	2	1	48	0.178	1.000
use for familiar routes	5	2	5	2	27.5	0.108	0.866
use for unfamiliar routes	6	1.75	7	1	64.5	0.042	0.380

As shown in Table D.7, a significant reduction in TCT was observed for the slider mechanism, indicating a modest block-level learning effect. No significant block differences were found for the checkboxes. Additionally, no significant block-wise differences were observed for Apply clicks for either mechanism.

Overall, these results suggest that general learning or order effects were limited and do not sufficiently explain the main performance differences reported between mechanisms.

D.3 Qualitative Coding Framework.

This section documents the qualitative analysis framework applied to open-ended questionnaire and interview responses. Table D.8 presents the finalized codebook, including code definitions used to guide the coding process.

To provide an overview of how frequently each code occurred in the dataset, Table D.9 reports code-level frequencies across all responses. These frequencies offer descriptive insight into which interaction experiences and reasoning patterns were most commonly expressed by participants.

Finally, Table D.10 aggregates code frequencies at the thematic level. These tables support transparency of the qualitative analysis and contextualize the interpretation of qualitative findings reported in the main text.

Table D.6: Mechanism comparison questionnaire responses (1 = strongly agree ... 7 = strongly disagree).

Item	Mean	SD	Median	IQR	W	p	r_{rb}
checkboxes allowed faster decisions	5.50	1.77	6.0	2.75	222	0.002	0.66
slider was easier to use	3.23	2.07	2.0	2.75	96.5	0.120	0.31
checkboxes were more confusing	2.12	1.40	2.0	1.00	13.5	0.000	0.80
slider felt more intuitive	4.46	1.94	4.5	3.00	165.5	0.204	0.27
slider better supported task goals	5.00	1.77	6.0	2.00	216	0.016	0.49
intention to use checkboxes	4.65	1.96	5.0	3.00	192	0.097	0.34
intention to use slider	4.65	2.19	6.0	3.75	183.5	0.161	0.29
slider preferred over checkboxes	4.46	2.18	5.5	3.75	189	0.262	0.23

Table D.7: Block-wise comparisons between Block 1 and Block 2 (independent groups; Wilcoxon rank-sum tests) for task completion time (TCT) and apply clicks.

Mechanism	TCT			Apply clicks		
	Median	W	p	Median	W	p
Checkboxes	$36 \rightarrow 29$	98.0	0.505	$4 \rightarrow 6$	65.5	0.335
Slider	$47 \rightarrow 29$	125.5	0.038	$6 \rightarrow 6$	79.5	0.815

Table D.8: Qualitative themes and codes used to analyze open-ended questionnaire and interview responses.

Theme	Code	Definition
Decision Strategies and Exploration	strategy_exploration	Describes how participants compare routes, rankings, or map features to make a decision.
	trial_and_error	Describes repeated adjusting of settings, experimenting, or iterative exploration.
	cross_view_linking	Reference to linking information across views (map, rankings, scores).
Mechanism Expressiveness	fine_grained_control	Refers to precise adjustment or flexibility in expressing preferences (e.g., percentages, sliders).
	feels_restrictive	Perception that the mechanism limits expression or choice.
Cognitive Effort and Ease	mental_effort	Explicit mention of thinking hard, cognitive load, or mental demand.
	easy_decision	Decision described as quick, intuitive, or effortless.
	confusion_about_scores	Uncertainty or confusion about how scores, weights, or rankings work.
Transparency and Trust	ranking_clarity	Rankings or scores are perceived as understandable and interpretable.
	black_box_feeling	System logic is perceived as opaque or unexplained.
	trust_in_system	Expression of confidence in the system's recommendations or outputs.
	lack_of_trust	Doubt or skepticism toward system recommendations.
	design_feedback	Suggestions or feedback about interface design.
Feature Salience, Constraints and Trade-offs	feature_preference	Preference for specific route attributes or features (not mechanism expressiveness).
	constraint_awareness	Explicit mention of remembering or prioritizing the task constraint.
	constraint_forgetfulness	Admission of forgetting or overlooking the constraint.
	speed_vs_experience_tradeoff	Explicit weighing of efficiency (time) against comfort, simplicity, or experience.
	context_dependent_usefulness	Perceived usefulness varies by situation (e.g., familiar vs unfamiliar routes).
	external_tool_comparison	Comparison with other navigation or routing tools.

Table D.9: Qualitative code frequencies across coded segments and unique participants.

Code	n_{segments}	$n_{\text{participants}}$
feature_preference	105	26
easy_decision	91	24
design_feedback	80	25
fine_grained_control	75	23
mental_effort	58	21
context_dependent_usefulness	56	26
speed_vs_experience_tradeoff	51	24
ranking_clarity	37	19
strategy_exploration	36	19
trust_in_system	36	20
cross_view_linking	27	22
feels_restrictive	27	17
confusion_about_scores	21	12
constraint_awareness	16	10
trial_and_error	13	11
lack_of_trust	13	10
black_box_feeling	6	6
external_tool_comparison	4	4
constraint_forgetfulness	4	3
ease_of_use	1	1

Table D.10: Theme coverage summary across coded segments and unique participants.

Theme	n_{segments}	$n_{\text{participants}}$
Feature Salience, Constraints and Trade-offs	236	26
Transparency and Trust	172	26
Cognitive Effort and Ease	171	25
Mechanism Expressiveness	102	24
Decision Strategies and Exploration	76	25

Appendix E

Ethics Documentation

Statement of the researcher

(to be signed and stored together with Informed Consent Forms)

This procedure, including the Ethics-App is intended only as a guideline to research-active students and employees of the Institute supervising the research. The responsibility for the wellbeing of research participants lies on the side of the researcher. Any uncertainties must be discussed with the Ethics Committee. Research approval is granted conditional to the following provisions:

1. Before the study begins, you are obliged to present the Participant with an Informed Consent Form (a template is automatically generated based on the data supplied to the Ethics-App).

2. You are obliged to collect a signed copy and keep it for reference as well as to provide the participant with a signed copy of the Informed Consent Form.

3. You are obliged to allow the participant to quit the study at any point with no further consequences. If applicable, payment is still due if the participant decides to withdraw his or her data at the end of the study (i.e. during the de-briefing phase).

4. You are obliged to follow the Institute procedure with regard to the handling of sensitive private data.

5. If the study involves collection of information without obtaining prior consent from some participants (e.g. public observation of human behaviour) information allowing the researcher to potentially identify or harm the person cannot be collected (e.g. many big data studies, street surveys). **Observations and recordings of public behaviour without consent can only occur if people can be reasonably expected to be observed by strangers at the given place and time** (with respect to the local cultural norms).

6. People have the right to know who is observing them in non-public situations (such as a meeting room, a laboratory). This right must be respected.

7. If your study involves your own students, declining participation cannot be linked (formally or informally) to the course grading scheme. If participation in the study is rewarded with credit points, alternative means of obtaining the same number of points at the comparable time expense and effort must be made available.

8. I confirm I will provide de-briefing information based on the below form either verbally or in written form to all participants of the study.

Date	Signature of researcher

Informed Consent Form

Study title: Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation

Revision: 2

Dear Participant,

thank you for your participation in the study.

Researcher(s):
Margaux Elijah Neri <mneri@unimuenster.de> (Master's Student, Geospatial Technologies) Thesis supervisors: 1. Prof. Christian Kray <c.kray@uni-muenster.de> (Institute for Geoinformatics (ifgi), University of Münster) 2. Dr. Simge Oktay<simge.oktay@uni-muenster.de> (Institute for Geoinformatics (ifgi), University of Münster) 3. Prof. Carlos Granell Canut <carlos.granell@uji.es> (Dep. de Llenguatges i Sistemes Informàtics, Universitat Jaume I)

Purpose of the study:
The purpose of this study is to understand how people use a cycling route-planning dashboard and how different ways of adjusting route preferences affect the user experience. You'll try out a prototype interface, make a few route-choice decisions, and share your thoughts about the experience. Your input will help us improve the design and usability of future tools that support cycling navigation.

Procedure:
You will be asked to use a cycling route-planning dashboard and complete a set of short tasks where you choose between route options. Before starting, we will walk you through how the interface works and give you a short practice round. As you work through the tasks, you will interact with the prototype and make route selections based on the information shown on the screen. After completing the tasks, you will answer a few short questionnaires about your experience. We will also have a brief conversation at the end to hear your thoughts and suggestions. The session will be recorded to help us review how people interact with the dashboard.

Duration:
30-45 minutes

Potential risks:
This study involves very minimal risk. Still, a few minor discomforts are possible: 1. Visual fatigue from looking at the screen for an extended period. 2. Cognitive fatigue from completing tasks that require some attention and concentration. 3. Possible discomfort being video-recorded. 4. Minor frustration during tasks if participants find parts of the

interface unclear or challenging to use. There are no physical activities or sensitive materials involved. Participants are free to pause or stop at any time if they feel uncomfortable.

Privacy:
Original data obtained from this study will be anonymised and only processed to draw scientific conclusions about groups, not about individual participants. Anonymised data might be published in academic journals, presentations, open science data repositories, or other media, but not in a way that would allow individual identification. One week after the completion of the study it might no longer be possible to retract your data from such aggregated analyses. You can contact the researcher in order to access your data or request its removal.

Benefits:
The participant will get 10€ as a reward at the end of the study.

You are free to stop, quit the study and retract your data **at any time during the study** with no further consequences.
If you have any questions, please ask them now.

For further questions, complains or issues, please contact the institute's Ethics-Committee: <ifgi-ethics@listserv.uni-muenster.de>.

▢ I confirm I volunteered to participate in this study.

▢ I confirm I was allowed to ask questions and that I was provided with responses.

▢ I confirm I was presented with this document prior to the beginning of the study.

▢ I confirm and I understood my right to quit the study at any time.

▢ I agree to be audio recorded during the study.

▢ I agree to be video recorded during the study.

Date

Signature of researcher

Signature of participant

Email address (optional)

(Please provide your email address if you would like to be informed about future studies)

▢ I have read the data protection statement for Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation and hereby voluntarily consent to having my personal data collected and processed as described in the statement. I have been informed of the right to withdraw my consent at any time without giving reasons.

Signature of participant

Data protection policy in accordance with Art. 13 GDPR and consent form

Project/reason: Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation

Revision: 2

1. Name and address of the responsible controller
The responsible controller as defined in the EU General Data Protection Regulation (GDPR) and other national data protection laws of the EU member states as well as other data protection-related provisions is:
Universität Münster / University of Münster represented by its Rector Schlossplatz 2, 48149 Münster, Germany
tel.: + 49 251 83-0
email: mailbox@uni-muenster.de

If you have any questions about the project, please contact the responsible staff member:
Margaux Elijah Neri <mneri@unimuenster.de> (Master's Student, Geospatial Technologies)
Thesis supervisors: 1. Prof. Christian Kray <c.kray@uni-muenster.de> (Institute for Geoinformatics (ifgi), University of Münster) 2. Dr. Simge Oktay<simge.oktay@uni-muenster.de> (Institute for Geoinformatics (ifgi), University of Münster) 3. Prof. Carlos Granell Canut <carlos.granell@uji.es> (Dep. de Llenguatges i Sistemes Informàtics, Universitat Jaume I)

2. Contact data of the Data Protection Officer
You can contact the Data Protection Officer at:
Data Protection Office
Schlossplatz 2, 48149 Münster
tel.: + 49 251 83-22446
email: datenschutz@uni-muenster.de

3. Data processing in connection with Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation
The purpose of this study is to understand how people use a cycling route-planning dashboard and how different ways of adjusting route preferences affect the user experience. You'll try out a prototype interface, make a few route-choice decisions, and share your thoughts about the experience. Your input will help us improve the design and usability of future tools that support cycling navigation.

a) Scope of data processing
The following personal data is processed in connection with Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation:

(1) first and last name
(2) date of birth
(3) email address and phone number

b) Purposes of data processing

The personal data listed above is processed for the purpose of carrying out the project Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation.

The personal data listed above will be used to draw scientific conclusions about groups, not about individual participants. Anonymised data might be published in academic journals, presentations, open science data repositories, or other media, but not in a way that would allow individual identification. One week after the completion of the study it might no longer be possible to retract your data from such aggregated analyses.

c) Legal basis for processing personal data

Your consent serves as the legal basis for processing your personal data listed above by the University of Münster, as stipulated by Art. 6 (1, 1a) GDPR and, if applicable, Art. 9 (2a) GDPR.

d) Further recipients of your personal data

Your personal data will neither be shared with other recipients within the University of Münster nor with recipients outside the University.

e) Duration of storage of personal data

The personal data listed above is stored for as long as necessary for carrying out the project Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation but shall not exceed 12 years. Upon withdrawing your consent, we shall delete your personal data.

4. Your rights as a data subject

You have the right to information about your personal data processed by the University of Münster (Art. 15 GDPR), the right to rectification (Art. 16 GDPR), erasure (Art. 17 GDPR), restriction of processing (Art. 18 GDPR) and the right to withdraw prior consent to such processing (Art. 7 (3) GDPR).

You may withdraw your consent in writing or by email from the contact persons listed under nos. 1 and 2 (see above) of this data protection statement.

You also have the right to lodge a complaint with the supervisory authority. The responsible supervisory authority is the Landesbeauftragte für Datenschutz und Informationsfreiheit Nordrhein-Westfalen, Postfach 20 04 44, 40102 Düsseldorf, tel: +49 211 / 38424-0, email: poststelle@ldi.nrw.de

Declaration of consent

Subject/reason: Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation

Full name: ____

Date of birth: ____

(if applicable) Name of parent or legal guardian:
____

Email address: ____

With your consent, you hereby grant permission to the University of Münster to collect and process the personal data listed above under (3a) for the purposes indicated in (3b).

You have the right to withdraw your consent from the responsible party at any time. The legality of all data processing from the time of consent until withdrawal of consent remains unaffected.

With your signature, you indicate confirmation of the following:
"I have read the data protection statement for the project Designing an Interactive, Weight-Adjustable Dashboard for Communicating Efficiency and Experiential Trade-Offs in Cycling Navigation. I hereby voluntarily consent to having my personal data collected and processed. I have been informed of the scope and purpose of data collection and processing, as well as the right to withdraw consent. I have received a copy of the data protection policy and the declaration of consent."

(if applicable) I confirm that I hold sole custody of the underage person named above – or in the case of joint custody – that I am permitted to grant consent on behalf of the other legal guardian or custodial parent.

City, Date: ____

Signature: ____
(consenting party)

(if applicable) Signature of the parent or legal guardian:
____

Debriefing Information

(to be prepared in written form or provided verbally to all participants after the study)

1. Disclose other experimental conditions (if there were any).

2. Disclose deception (if there was any).

3. Correct any misconception that the participant might have if you are aware of any.

4. List your hypotheses (if applicable).

5. **Remind about the right to retract data now** (if applicable, payment still is due).

6. Provide a website with the description of the research project and other relevant resources (if applicable).

7. Provide your business card / contact information.

8. **DO NOT** talk of some patterns of the studied behavior being more plausible (or expected) than others.

(no signatures required)

Masters
Program
in **Geospatial**
Technologies

Designing and Evaluating an Interactive Dashboard for Communicating Efficiency–Experiential Trade-Offs in Cycling Route-Planning

Margaux Elijah Neri

Dissertation submitted in partial fulfilment of the requirements
for the Degree of *Master of Science in Geospatial Technologies*

NOVA IMS Information Management School
Universitat Jaume I
Universität Münster