INSTITUTE OF COGNITIVE SCIENCE
OSNABRÜCK UNIVERSITY

MASTER'S THESIS

A thesis submitted in fulfillment of requirements for the degree of Master of Science

A Comparative Experimental Study of Static and Interactive Maps in Visualizing Travel Experiences Using Public Transportation

by
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Submitted: July 16, 2025

Declaration of Authorship

I, Febryeric Malsom Parantean, hereby certify that the content of this thesis represents my own knowledge, my own understanding, and my own perspective on the topic. In case artificial intelligence tools were used, their way and purpose of usage has been made transparent. Moreover, I have cited all my sources by academic standards. This thesis has not been submitted, either in part or whole, at this or any other university.

Osnabrück, July 16, 2025,

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Abstract

Data visualization is a necessary approach to enhance human understanding in visual representation from a collected dataset. However, when working with complex spatiotemporal datasets, circle maps or dot visualizations lead to a cluttered appearance. This study proposes a hexagonal interactive map as a solution to avoid overloaded visualization. The interactive map in this study contains three main features: filter, histogram, and brushing extension. To evaluate the interactive map, this study also included the static map as a comparison. The two main variables in this study are accuracy and user experience. The interactive map was developed with D3 libraries and a React application, whilst the static map was created with QGIS software. The dataset from a previous study regarding travel experience with public transportation was used in the map. This study employed a within-participant experimental design. There were 14 participants in total with varying educational backgrounds, genders, ages, and nationalities. The experiment was fully online, and each participant examined both the map and filled in the questionnaires related to the information on the map to measure accuracy, and also their experience when working with both maps. As a result, the interactive map had slightly less score in accuracy, even though outperformed in user experience score compared to static map. The static map can perform better in the browser without rendering time; however, this map was lack of interaction and the ability to explore the data in more detail. In contrast, even though the interactive map needed a longer time to load the interface, the majority of the participants preferred this map. This was due to the ability of the interactive map to present the visualization with varying combinations of parameters, either in fragments or as a complete whole.

Keywords: Data visualization, interactive map, hexagonal map, user experience, travel experience

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List of Abbreviations

AI Artificial intelligence

CSS Cascading style sheets

DOM Document object model

ECG Electrocardiogram

GIS Geographic information system

GPS Global positioning system

HRMAD Heart rate mean absolute deviation

HRV Heart rate variability

HTML Hypertext Markup Language

OSM Open street map

PNG Portable network graphics

QGIS Quantum GIS

RQ Research question

SD Standard deviation

VR Virtual reality

UI User interface

UX User experience

D3 Data-driven documents

2D Two-dimensional

Chapter I
Introduction

The rapid development of digital sensors and real-time data collection technologies has led to an increasing demand for visual communication and interpretation. This has been taking place in domains such as transportation, urban planning, and landscape design, where human activities, emotions, and subjective experience can also be measured (Bleisch & Hollenstein, 2018; Meenar et al., 2019; Han et al., 2025).

Effective visualization refers to the process of interpreting raw information into visual formats such as maps, charts, or dashboards, to enhance human understanding, communication, and decision-making (Srinivasa et al., 2021; Pauliková, 2022). Traditional visualizations, such as bar charts and static choropleths, do not always meet the demands. Presenting multimodal, complex, and high-frequency datasets produced by, for example, intelligent vehicles, mobile sensors, and participatory platforms requires advanced visualizations (Sun et al., 2020; Nguyen et al.,2018). In other words, visualization is not merely reporting outcomes, but rather a cognitive interface for exploring the relationships between time, space, and human experience. Therefore, this has led to the evolution of geovisualization, an interdisciplinary practice with the combination of cartography, human computer interaction, psychology, and computational design to support spatial reasoning and storytelling in visualization (Pettit et al., 2012; Thöny et al., 2018).

1.1. Geovisualization

Geovisualization is a necessary approach for interpreting complex spatial patterns and phenomena. It integrates Geographic Information System (GIS), computer graphics, visual analytics, and cognitive science to enhance human understanding of geospatial data (Çöltekin et al., 2018; Sibolla et al., 2018). Geovisualization extends into thematic and hierarchical representation of spatial patterns through hexagonal cartograms (Barreto et al., 2018) and cognitive visualization frameworks (Balla et al., 2017). For instance, Zhu (2007) emphasized measurable visual efficiency, and Davidson et al. (2023) provided a model for quantifying user enjoyment, applicable in data dashboards and social maps (Cardone et al., 2023).

One significant area of development within geovisualization is affective or emotional mapping, which tries to identify, capture, and represent the feelings associated with the space and movement. For instance, travel is studied not only as physical displacement from one point to another point, but also as an affective journey that is related to emotions such as stress, joy, fear, and belonging (Bleisch & Hollenstein, 2018; Meenar et al., 2019; Burgos-Thorsen, 2025). Spatial contexts, socio-political conditions, and cultural identities influence these emotional dimensions. The visualization methods have responded by incorporating color, valence, and symbolization strategies that communicate these emotional dimensions (Bleisch & Hollenstein, 2018; Park et al., 2020).

1.2. Previous studies

The evolution from static maps to dynamic, exploratory platforms is well-documented (Cook et al., 2016; Mayer et al., 2023), highlighting a broader shift from passive to active user-driven exploration in geovisualization. Cook et al. (2016) emphasize that the interactivity allows users to explore, filter, and manipulate large datasets for deeper analysis. Immersive Virtual Reality (VR) applications by Donalek et al. (2014) offer new cognitive and collaborative possibilities. This study expands the boundaries of visual analytics by enabling users to interact with multi-dimensional data in a collaborative virtual environment.

Bresmenev et al. (2022) further emphasize the importance of real-time visualization in mobile applications, supporting decision-making and situational awareness, specifically in environmental monitoring and urban planning. Birch et al. (2007) demonstrate how geovisual tools aid in environmental data interpretation. Edwards and Nelson (2001) and Pleil et al. (2011) applied visual methods to chemical and environmental data, enhancing interpretability in supporting regulatory and public health decision-making.

A recent study by Bosch et al. (2025) integrated biometric data into mobility studies to gain a better understanding of travel experience by using public transport. As an interactive visualization, the study used R Shiny interfaces to show relevant information regarding travel experience, for instance, stress level, level of journey satisfaction, Heart Rate Variability (HRV), and Heart Rate Mean Absolute Deviation (HRMAD). In addition, Park et al. (2020) and Han et al. (2025) used emotion-mapping frameworks in leisure and urban design settings. These methods offer insights into user experience that extend beyond traditional measurements like travel time or distance. These studies highlight the increasing importance of sensor-based, emotion-rich data and suggest the need for new visual frameworks that support exploration without overwhelming users.

However, visualizing such high-frequency and emotion-laden datasets presents design challenges. The majority of them are visual clutter and information overload. Traditional dot maps often become unreadable when representing overlapping data points or extended time series. As a solution, researchers have increasingly adopted hexagonal binning, a method that tessellates geographic space into uniform hexagonal cells to reduce overlap and enhance perceptual clarity (Pánek, 2018; Arbex & Cunha, 2020; Karsznia et al., 2021).

While dot maps may be intuitive for sparse distributions, they quickly become unreadable in urban centers compared to hexagonal maps that provide a visually stable alternative that supports both cognitive interpretation and cartographic fairness (Barreto et al., 2018). They found that hexagonal cartograms use fixed-size units to improve visual clarity and comparison. By standardizing geometry and balancing layout, the approach supports more reliable multi-subject educational mapping, offering a visually stable framework particularly effective in avoiding the perceptual distortions common in traditional thematic maps. Gunawan and Susilawati (2021) also found hexagonal bins effective in clustering spatial demand in mobility-on-demand contexts, reinforcing their utility in dense urban visualizations.

1.3. Present study

In this present study, the author proposes a different approach with hexagonal maps as data visualization to portray spatiotemporal data, which consists of subject experiences. In addition, this study proposed an interactive map with a hexagonal map and compared it to a static map. The static map was created in Quantum GIS (QGIS)[1] software. QGIS offers high-resolution, cartographically curated snapshots suitable for printed or offline analysis (Szombara, 2021). This map is particularly effective in communicating a fixed story or summary of spatial trends. On the other hand, the interactive visualizations let users change the data view, apply filters, and explore information in real-time, built with JavaScript libraries like Data-Driven Documents (D3)[2] (Sun et al., 2020). These features can improve engagement of the users, but they may also create challenges in cognitive load, especially for users with lower spatial understanding (Thöny et al., 2018; Willigen, 2019). Therefore, the interactive map in this study was developed with the D3 library with a React application[3].

Despite these technological advancements, there is still limited empirical research comparing static and interactive maps when visualizing spatiotemporal physiological data, particularly using consistent geometrical frameworks like hexagonal grids. Most prior studies focus on either usability or technological performance, without evaluating how these

[1] https://qgis.org/
[2] https://github.com/d3/d3
[3] https://reactjs.org

interfaces affect users' cognitive interpretation and emotional engagement (Mayer et al., 2023; Gleicher et al., 2011).

In this study, two variables were assessed, which were the accuracy and the user experience. The accuracy refers to comparing the D3 map as a proposed interactive map to QGIS as an open-source software for geovisualization. Although the maps' accuracy was not directly assessed, how precisely the maps could present the visualization from the datasets, this study was more focused on portraying the data in similar shapes and intervals or ranges of values of the datasets within the color scale.

Benduch (2017) examined between ARcGIS[4] and QGIS and found that both ArcGIS and QGIS achieved nearly identical outcomes for vector-based spatial operations. However, there are still no empirical findings to compare the static and interactive maps produced by D3 with open-source geovisualization software such as QGIS or ArcGIS.

1.4. Research questions and hypotheses

Therefore, this study is guided by two research questions (RQs) and their hypotheses:

1) ***Is there a significant difference in accuracy between the static and interactive maps?***
    - *H_0: There is no significant difference in accuracy between the static and interactive maps.*
    - *H_1: There is a significant difference in accuracy between the static and interactive maps.*
2) ***Do the static and interactive maps lead to significantly different user experiences?***
    - *H_0: There is no significant difference in user experience between the static and interactive maps.*
    - *H_1: There is a significant difference in user experience between the static and interactive maps.*

These research questions are investigated with the data collection from Bosch et al. (2025). The dataset was collected from 44 participants who navigated a 15 km route using various modes of transportation: tram, bus, and train. During travel, the participants' Global Positioning System (GPS) location and heart rate were captured every second by an electrocardiogram (ECG) belt. Additionally, the stress level, journey satisfaction, and

[4] https://www.arcgis.com/index.html

emotional responses were measured via questionnaires every 3.5 minutes using an equipped mobile phone.

The next chapter combined the literature review and related work, which contains concepts in the static and interactive maps, the hexagonal map, accuracy, and user experience. Chapter 3 explains the research methodology, including research instruments, participants, and experimental procedure. Chapters 4 and 5 focus on experimental results and discussion, and finally, Chapter 6 contains the conclusion of this study.

Chapter II
Literature Review and Related Work

2.1. Static and interactive maps

According to Mitchell (2005), the classification of static and interactive maps depends on their interactivity degree. Static maps provide effective tools for presenting summarized information, particularly in printed reports or posters. Static maps, often used in traditional infographics, present information in a fixed, author-driven format designed to convey a specific narrative to the reader (Rodríguez et al., 2015). They also state that the main distinction between static and interactive maps lies in user control: static maps are author-driven, presenting a fixed narrative, while interactive maps are reader-driven, enabling free exploration. Similarly, Cook et al. (2016) argue that static maps may oversimplify complex data, limiting the user's ability to explore or question the underlying patterns, whilst interactive maps serve as exploratory tools, allowing users to manipulate data, change views, and uncover hidden relationships not visible in static displays

Moreover, interactive maps can be implemented to meet diverse user needs, whether novice or expert. They are particularly useful in participatory mapping, decision support, and public communication of scientific results (Davidson et al., 2023; Wallner & Kriglstein, 2020). By integrating user inputs and custom filters, interactive maps improve comprehension, memorability, and even trust in the data being presented. This user adaptability is essential in fields such as public health (Javaheri, 2021) and urban planning (Calle-Jimenez et al., 2019), where diverse audiences interpret maps with varying levels of expertise.

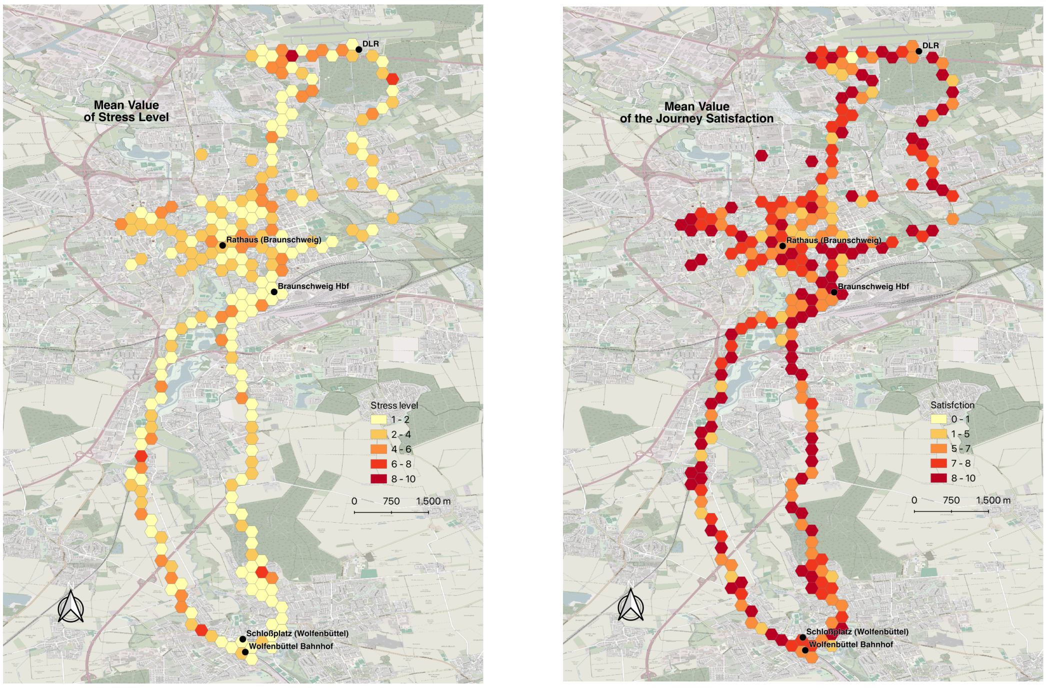
In this study, static and interactive maps were examined. The static map was created by QGIS, and the interactive map was developed by D3 with a React application. According to Khan & Mohiuddin (2018), the QGIS application was designed to present and analyze geospatial data. The QGIS software can be operated on multiple operating systems such as Windows, macOS, and Linux. According to Zauner (2019), D3, developed by Mike Bostock[5] in 2011, is a JavaScript library that was designed to attach data to the Document Object Model (DOM) and convert it into a dynamic, data-driven visualization. On the other hand, React[6] is a component-based JavaScript library originally developed by Jordan Walke, which

[5] https://d3js.org/
[6] https://reactjs.org

focuses on building flexible user interfaces and simplifies user interface (UI) development through its virtual DOM (Zauner, 2019).

To create the static map with hexagonal shapes in QGIS, first of all, the hexagonal shape pattern needs to be created. The size of the hexagonal shape can be adjusted before it is rendered. Once the hexagonal shapes were rendered, the next step was to integrate the dataset with the appropriate hexagonal shape coordinates. In this part, which value from the data set that needs to be presented must be chosen, for example, the stress level. Once the rendering finishes, the color and legend need to be adjusted. Since this study evaluated only four variables from the dataset: HRV, HRMAD, stress level, and journey satisfaction, each map needs to be rendered one by one and finally converted to a Portable Network Graphics (PNG) as a static map. Figure 2.1 shows an example of the static maps interface in this study.

Figure 2.1: The static maps of HRV and journey satisfaction.



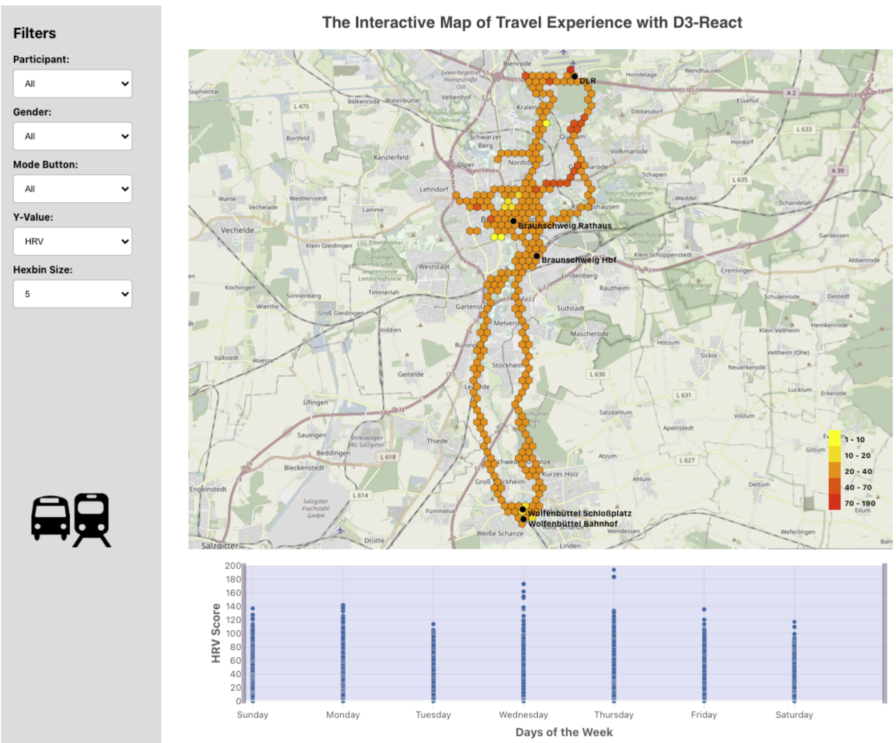
Developing the interactive map[7] needs a different approach since it was developed with two programming languages, JavaScript and Cascading Style Sheets (CSS). The author used Visual Studio Code as the Integrated Development Environment (IDE). The map was inspired by Morgan[8] (2018) and Kelleher[9] (2019).

[7] https://fmparantean.github.io/datavis_map/
[8] https://github.com/jeffreymorganio/d3-geo-hexbin
[9] https://vizhub.com/curran/multiple-views-with-brushing

In this study, the interactive map had three main features: the hexagonal map, brushing tools in the histogram, and filters. Each feature was created in a different file and integrated into one file to run all the code. These features were mostly built with the JavaScript programming language, with D3 and React libraries. Even though the Hypertext Markup Language (HTML) has also been used in the React application, however, React does not allow for changing the HTML part. To finalize the interface, the CSS programming language was used. While developing the interactive map, the author also used ChatGPT as an artificial intelligence (AI) tool to solve some parts of the code.

On the filter feature, there were five options menu: participant, gender, mode button, Y-Value, and hexbin size. The users can choose which participants' data to be displayed on the hexagonal map. The option can be "all participants" or individual, from participant one to participant 44. The gender and mode button options were to display the participants' gender and the type of transportation mode used. The Y-value option allows users to choose which data points will be presented in a histogram and project them into the hexagonal map based on the variables from the data set. In this study, the Y-values included HRV, HRMAD, stress level, and journey satisfaction. The brushing feature allows users to mark which data points need to be displayed on a specific day or an entire week. Finally, the hexbin size option was to adjust the hexagonal size on the map. Figure 2.2 shows the interface of the interactive map in this study.

Figure 2.2: The interactive map interface with filters, histogram, and hexagonal shapes.



2.2. Hexagonal maps: avantages and disadvantages

Compared to dot or circle maps, which may lead to overlapping points and clutter (Sanyal et al., 2009), hexagonal bins manage data density better. Circle maps often misrepresent data magnitude or spatial relations. However, hexagonal maps require projection correction (Battersby et al., 2017), and users may misinterpret counts if the bins are not clearly labeled (Gleicher et al., 2011). Hexagonal binning improves spatial representation by reducing edge bias, preserving isotropy, and enhancing pattern clarity (Battersby et al., 2017; Hales, 2001).

Compared to square grids or dot maps, hexagons avoid alignment artifacts and are better for density mapping. Javaheri (2021) found that hexbin maps outperformed choropleths in conveying COVID-19 mortality in Mexico. Polisciuc et al. (2016) and By (2021) show hexbin maps allow fairer spatial aggregation in business intelligence and epidemiology. The honeycomb structure's mathematical efficiency is proven by Hales (2001), while Cook et al. (2016) warn of perceptual pitfalls with poorly scaled bins. Wallner & Kriglstein (2020) discuss the challenge of maintaining clarity across zoom levels. However, the zoom option on this study was not available.

2.3. User experience

User experience (UX) is key to the design and success of geovisualization systems. According to Çöltekin et al. (2019), effective geovisual tools should accommodate users' perceptual and cognitive abilities, reduce cognitive load, and support intuitive exploration. Koua and Kraak (2004) introduced a usability framework that assesses visualization systems based on effectiveness, efficiency, and user satisfaction. Similarly, Wang et al. (2021) propose a user experience model that integrates visual clarity, emotional engagement, and functionality. Lefebre et al. (2008) highlight how different display types influence user interpretation.

Narrative and interface design are crucial aspects of the UX. Mayer et al. (2023) found that data stories using scrollytelling and timeline structures improve users' understanding and retention. Rodríguez et al. (2015) support the use of narrative structures that guide readers through spatial stories. Passera (2012) discusses how visual contracts enhance comprehension in legal and business contexts. Saket et al. (2016a) and Saket et al. (2016b) show that visual shape and layout significantly impact users' ability to interpret map content accurately. Additionally, Sharif et al. (2021) emphasize accessibility concerns for screen-reader users engaging with online visualizations.

Empirical studies highlight the impact of UX on various user groups. Robinson (2017) and van Willigen (2019) explore how spatial literacy and map legibility influence user interaction. Karsznia et al. (2021) examine usability challenges with statistical maps, especially when conveying uncertainty. Wallner and Kriglstein (2020) investigate interaction design in location-based apps. Davidson et al. (2023) introduce the ENJOY scale to evaluate emotional and cognitive experiences, linking affective responses to design elements. Zhu (2007) and Willigen (2019) demonstrate that well-structured layouts and clarity improve UX even for novice users.

2.4. Accuracy in map comparison

Map accuracy encompasses spatial precision, visual clarity, and interpretative correctness. Balla et al. (2022) employed statistical tests like the Wilcoxon test to validate water quality data visualizations. Çöltekin et al. (2019) emphasize that perceived accuracy is often shaped by interface clarity and user cognition rather than just data quality. Saket et al. (2016b) and Sanyal et al. (2009) studied how different shapes and uncertainty indicators impact interpretive accuracy.

Furthermore, Gleicher et al. (2011) and Szombara (2021) stress that accuracy in comparative tasks depends on layout design, normalization, and legend clarity. Donalek et al. (2014) found that VR platforms improved users' spatial awareness and performance in geospatial comparisons compared to two-dimensional (2D) interfaces. Overall, accuracy must be evaluated from both data and user-centered perspectives. Similarly, Zhu (2007) stated that a visualization is considered accurate when users can readily and correctly interpret the data with minimal perceptual or cognitive distortion. In addition, according to the author, effective maps should achieve a high correspondence between visual variables (e.g., color, size, position) and the actual data they encode.

Chapter III
Methodology

3.1. Research instrument

To answer the research questions, this study investigates the accuracy and user experience through two sets of questionnaires. The questionnaires were given during the experiments shortly after the maps were done to be examined. Both questionnaires contained similar items that related to the accuracy and the adapted ENJOY scale items to measure the experience of the participants. In addition, the second questionnaire included additional general questions that contained subjective experience during working with the static and interactive maps and the evaluation of the experiment setting.

3.1.1. Accuracy

The accuracy refers to the map accuracy between static and interactive maps. Since QGIS is open-source software and commonly used among researchers and practitioners, the interactive map that was developed with D3.js with React, on the other hand, needs to be evaluated. There were four "True or False" questions to measure the accuracy related to maps:

- The HRV scores are relatively similar when people were commuting with the bus and train between Braunschweig Hbf. and Wolfenbüttel Bahnhof.
- The stress level scores around Braunschweig Hbf. are middle-high (scale 6-8 out of 10)
- People are less satisfied when using the train than the bus during traveling between Braunschweig Hbf. and Wolfenbüttel Bahnhof, with the scores predominantly under 5 out of 10
- The HR_mad scores around Braunschweig Hbf. are significantly higher than Wolfenbüttel Bahnhof.

For each question, one point for the correct answer and zero points for the wrong answer, with a total maximum score were four.

3.1.2. Adapted ENJOY scale

Davidson et al. (2023) have developed and validated a new measure called the ENJOY scale that can be used in a wide range of contexts, particularly where a person's level of enjoyment is related to technology or interactively performed tasks. The ENJOY scale contains five motivational factors known as the Psychological Needs Satisfaction Scale: pleasure, relatedness, competence, challenge/improvement, and engagement. To provide confirmatory evidence on construct validity, the authors also provided evidence for reliability, which showed that the scale is highly efficient in measuring the fine-grained feelings users enjoy when interacting with screen-based content, such as visualizations. These results support the complexity of user enjoyment as a construct that potentially impacts users' involvement, motivation, and satisfaction with technology-driven activities. Table 3.1 demonstrates the subdimensions and their definitions (Saket et al., 2016b; Davidson et al., 2023).

Table 3.1: The subdimension definition of the adapted ENJOY scale.

Dimension	Definition
Pleasure	Corresponding feelings of happiness, fun, and overall satisfaction with the use of data visualization
Relatedness	Closeness or interaction felt by the users with other users during the activity. This can also include cooperational modes and social activities related to data visualization, including sharing ideas with colleagues, or joint working on data visualizations
Competence	Evaluates users' perceived behavioral control, or how well they can complete the task and tailor it to fit their use. Concerning data visualization, it means a set of postures that pertain to the level of competence users believe they harbor in generating, understanding, and interpreting these displays
Challenge/ Improvement	Identifies whether users consider the activity as being demanding sufficiently, and if they see chances to improve, respectively. In the context of data visualization, this means understanding that the tasks involve learning and cognitive development
Engagement	The level of usage interaction, or in other words, the extent to which the users are absorbed in the activity. It depicted how one can attend to data visualization in terms of time and a user's ability to block other stimuli from their field of view.

In this study, the adapted ENJOY scale was implemented as the research instrument to measure the UX of the participants while working with the static and interactive maps. Therefore, to align the items with this study, Table 1.2 shows the original items and the items for this study corresponding with each dimension of the ENJOY scale.

Table 3.2: The original ENJOY scale and adapted ENJOY scale.

Dimension	Original items	Items for this study
Pleasure	● The activity was pleasurable to me ● The activity made me feel happy ● The activity was fun ● I liked doing the activity ● The activity made me feel good	● I feel happy to analyze the data with this visualization. ● Finding information with this visualization was entertaining. ● From the tool, I enjoyed interpreting the results with this visualization.
Relatedness	● I felt connected with others during the activity ● I liked interacting with others during the activity ● I cooperated with others during the activity ● The activity was a shared effort with others ● I felt close to others when I did the activity	● I felt connected to the features of the data visualization interface while using it. ● I appreciated the layout and design of the data visualization tool during my interaction. ● The user interface made it easy for me to share insights and collaborate with others. ○
Competence	● I felt very capable during the activity ● I am good at the activity ● I felt like I did a good job the last time I did the activity ● I was proficient in the activity ● I felt competent in performing the activity	● I was able to use the visualization tools effectively ● I believe I could explain the data as presented in the visualization well. ● I felt confident that I was capable of analyzing the data visualization task that was
Challenge/ Improvement	● The activity allowed me to develop new skills. ● I felt challenged, but not over-challenged, during the activity ● I improved my skills the last time I did the activity ● During the activity, I could get better at doing it ● I felt challenged, but not under-challenged, during the activity	● The data visualization task was full of new lessons on analytical approaches. ● I felt challenged while working with the data visualization. ● I improved my understanding of the data while using the visualization.

Dimension	Original items	Items for this study
Engagement	● I lost track of what was going on outside of the activity ● I forgot what was going on around me during the activity ● I lost track of time during the activity ● When I did the activity, I thought about nothing else ● I lost track of what was going on around me during the activity	● I did not realize how much time was taken while interacting with the data visualization ● I managed to lose attention to my surroundings in the process of working on the data visualizations. ● My attention was fully directed to the details in the data visualization

The adapted ENJOY scale was used as a Likert scale ranging from one, strongly disagree, to five, strongly agree. The total score of each subdimension was 15 and 75 for the overall scale. Therefore, the adapted ENJOY scale items in this study were:

1) **Pleasure:** (1:strongly disagree to 5: strongly agree)
   - I feel happy to analyze the data with this visualization.
   - Finding information with this visualization was entertaining.
   - From the interface, I enjoyed interpreting the results with this visualization.
2) **Relatedness:** (1:strongly disagree to 5: strongly agree)
   - I felt connected to the features of the data visualization interface while using it.
   - I appreciated the layout and design of the data visualization tool during my interaction.
   - The user interface made it easy for me to share insights and collaborate with others.
3) **Competence** (1:strongly disagree to 5: strongly agree)
   - I was able to use the visualization tools effectively
   - I believe I could explain the data as presented in the visualization well.
   - I felt confident that I was capable of analyzing the data visualization task that was assigned to me.
4) **Challenge/Improvement** (1:strongly disagree to 5: strongly agree)
   - The data visualization task was full of new lessons on analytical approaches.
   - I felt challenged while working with the data visualization.
   - I improved my understanding of the data while using the visualization.

5) **Engagement** (1:strongly disagree to 5: strongly agree)
    - I did not realize how much time was taken while interacting with the data visualization
    - I managed to lose attention to my surroundings in the process of working on the data visualizations.
    - My attention was fully directed to the details in the data visualization

Finally, the subjective general questions were also employed at the end of the experiment. These questions assess direct comparison related to the static and interactive maps, and also the experimental setting for this study. The questions are:

1) Which data visualization do you like the most?
    - QGIS Map (static map)
    - D3-React Map(interactive map)
    - Both
    - None of Them

    Can you elaborate on your answer?
2) From your subjective experience, what are the advantages and disadvantages of using QGIS (the static map)?
3) From your subjective experience, what are the advantages and disadvantages of using D3-React (the interactive map)?
4) From your subjective experience, how do you describe your feelings of using QGIS (the static map)?
5) From your subjective experience, how do you describe your feelings of using D3-React (the interactive map)?
6) From one to five, what is your rating of the static map (QGIS)?
7) From one to five, what is your rating of the interactive map (D3-React)?
8) What is your suggestion that can be improved in presenting the data visualization in this experiment?
9) In general, what can be improved in this experimental setting?
10) In general, from one to five, what is your rating for this experimental setting?

3.2. Participant

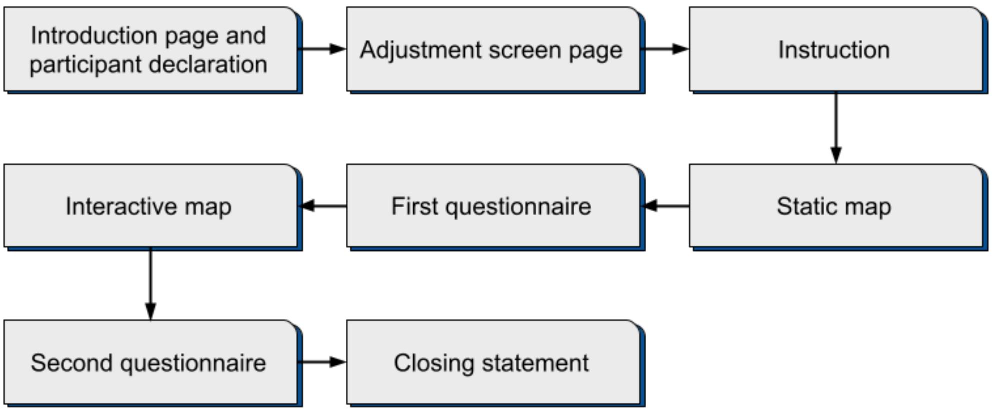
The study was conducted with 14 participants (six male and eight female) who fulfilled the criteria to be participants in this study. All the participants were over 18 years old, had no color blindness, and were not suffering from Trypophobia or fear of the hexagonal shape. The participants came from various backgrounds, such as educational level, profession, and nationality. Three of them were DLR's employees, four participants were cognitive science students at Osnabrück University, two participants were doctoral students at TU Berlin and TU Braunschweig, and the rest were practitioners in various fields such as cyber security, edu-tech, and a psychologist. The participants' nationalities were German, Indonesian, Russian, Polish, and Palestinian.

3.3. Experimental setting and procedure

This study used a within-participant experimental design. Each participant examined both static and interactive maps and then filled out the questionnaires. The experiment set was fully online. The experiment setting was created by the D3 library and React application and deployed with GitHub Pages[10]. The questionnaires were created with Google Forms[11], which were also integrated into the experiment setting alongside the static and interactive maps page correspondingly.

The experimental procedure setting can be seen in Figure 3.1. First of all, after the participants were given the link to participate in this experiment, they needed to fulfill the participant's criteria by clicking the criteria list to be able to continue the experiment. Second step, the participants need to adjust the screen monitor size to optimize the interface for this experiment. After that, the participants were given the instructions related to this experiment. The next step, the participants examined the static map and filled out the first questionnaire. After completing the first questionnaire, the participants examined the interactive maps, filled out the second questionnaire, and then they were allowed to finish the experiment[12].

Figure 3.1: Experimental procedure.



[10] https://pages.github.com/
[11] https://docs.google.com/forms
[12] https://fmparantean.github.io/datavis_thesis/

Chapter IV
Result

This chapter presents the statistical analyses between static and interactive maps from the experiment. Table 4.1 shows the overall result of variable measurement, including the sub-subdimension of the adapted ENJOY scale. The mean scores of the static and interactive maps alongside the standard deviation (SD), normality p value, significant test p values, and Cohen's d value are presented in the table.

Table 4.1: Statistical measurement of the accuracy and adapted ENJOY scale.

Measure	Static Map Mean (SD)	Interactive Map Mean (SD)	Normality (p)	p-value	Significant?	Cohen's d
Accuracy	3.357 (0.633)	3.143 (0.770)	0.0786	0.385	NO	0.240
ENJOY (Overall)	45.571 (8.653)	53.071 (9.794)	0.5060	0.062	NO	-0.545
Pleasure	9.214 (2.517)	10.643 (2.951)	0.9729	0.216	NO	-0.348
Relatedness	8.714 (2.730)	11.429 (2.533)	0.3078	0.026	YES	-0.671
Competence	9.429 (2.102)	11.714 (2.867)	0.0690	0.032	YES	-0.642
Challenge/Improvement	10.357 (2.468)	10.357 (2.170)	0.5321	1.000	NO	0.000
Engagement	7.857 (2.598)	8.929 (3.430)	0.2452	0.132	NO	-0.429

4.1. Accuracy

To measure the accuracy of the maps, there were four binary questions regarding the presented visualization. The total score was four, with each question having one point for correctness. As a result, the static map outperformed the interactive map with a slightly higher score. The participants reached 83.9% correctness (mean score: 3.357; standard deviation: 0.633) for the static map and 76.6% correctness (mean score: 3.143; standard deviation: 0.770) for the interactive map (Figure 4.1).

The p-value from the Shapiro-Wilk test for normality shows the accuracy score of 0.0786, which means the data were considered to be normally distributed (Figure 4.2). Since the data was normally distributed, a paired t-test was deployed to determine if the maps were significantly different. As a result, there is no statistically significant difference between the static and interactive maps' accuracy, with the p-value of 0.385 and Cohen's d score of 0.240.

4.2. User experience

The adapted ENJOY scale in this study consists of 15 items, divided into 5 subdimensions: pleasure, relatedness, competence, challenge/improvement, and engagement. As the Likert scale was used for scoring, the score was in the range of 15 to 75. The result shows that the interactive maps acquired a score about 8 points higher than the static map, with 45.57 (standard deviation: 8.653) for the static map and 53.07 points (Standard deviation: 9.749) for the interactive map (Figure 4.3).

Figure 4.1: Accuracy correctness comparison of static and interactive maps.

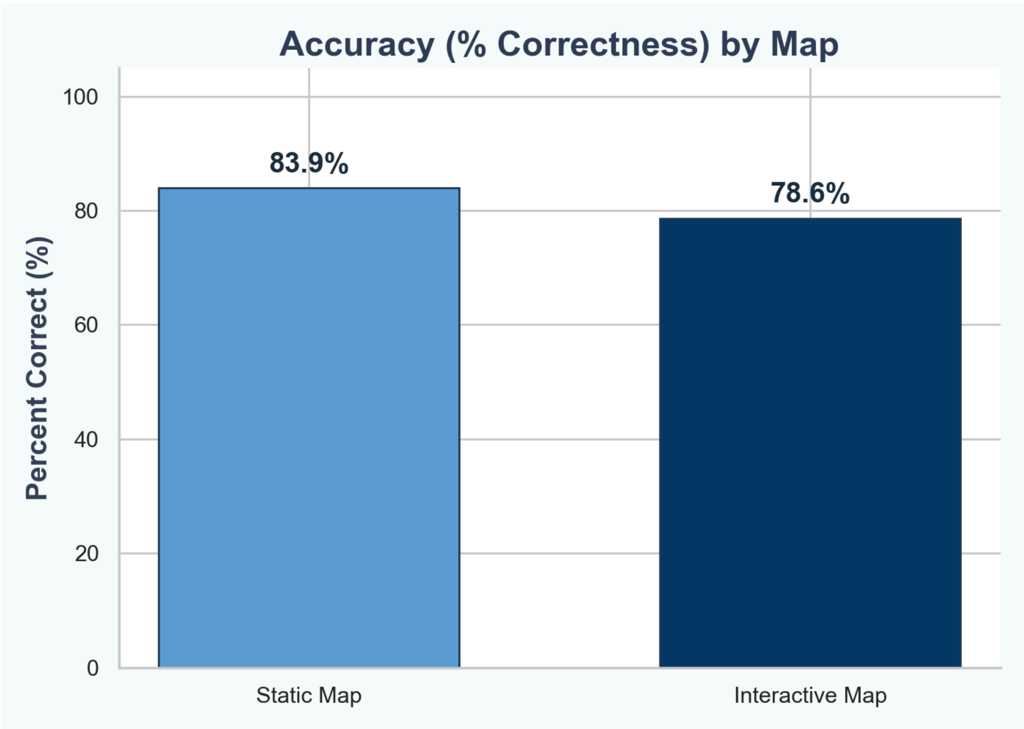
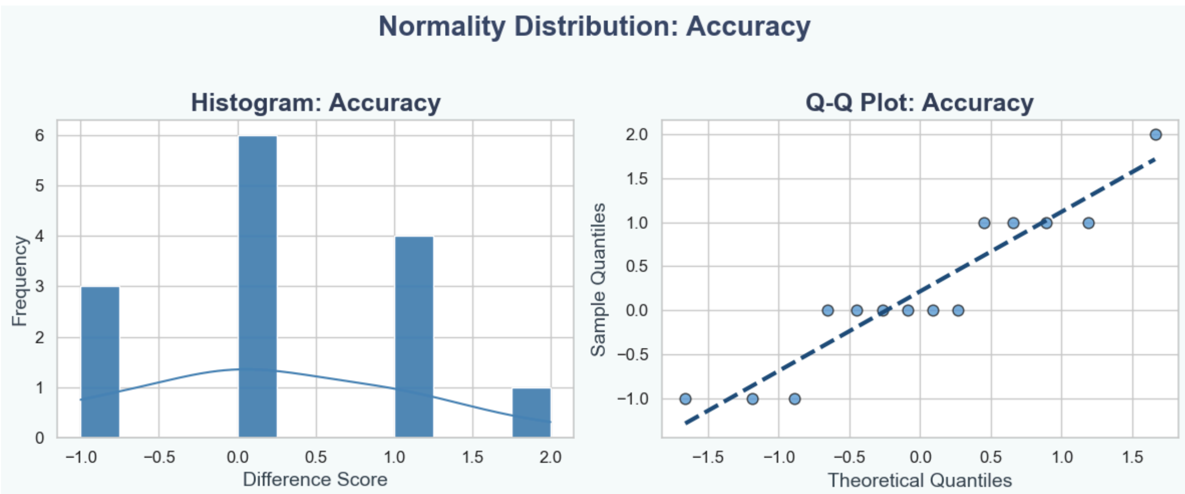
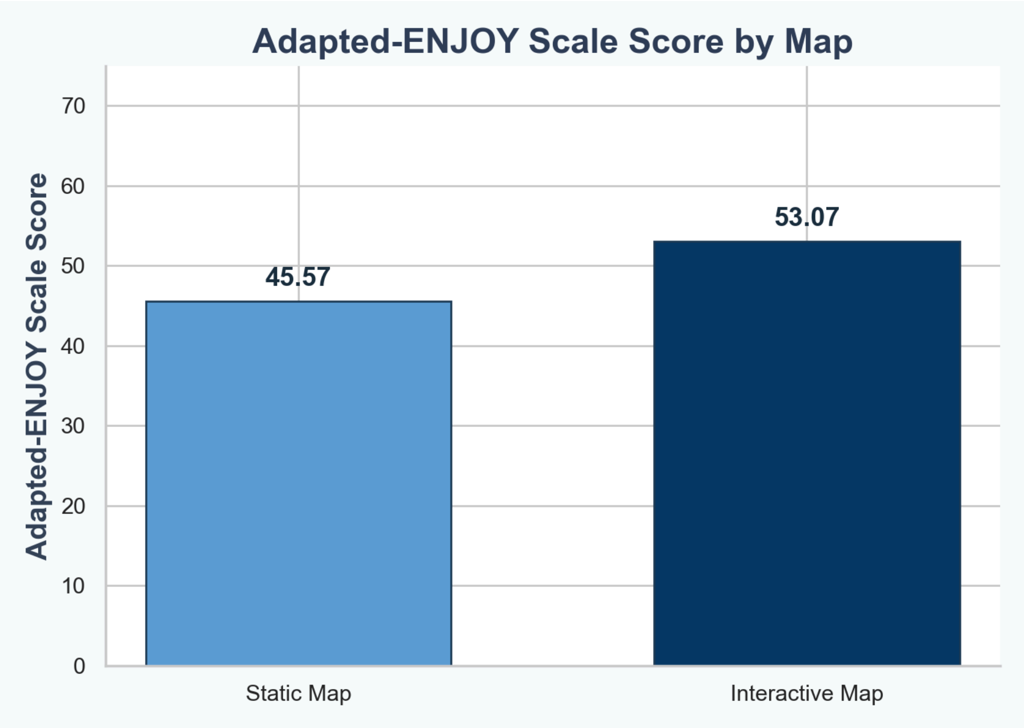


Figure 4.2: Data distribution of mean accuracy scores.



To find the appropriate significant test, one needs to determine the data distribution with the Shapiro-Wilk test (Figure 4.4). The normality p-value shows the adapted ENJOY scale score of 0.506. The data were normally distributed; therefore, a paired t-test was used to determine if the adapted-ENJOY scale mean score was significantly different between the static and interactive maps. As a result, the p-value showed 0.062, with Cohen's d score showing -0.545, which means there was a significant difference related to the participants' experiences

Figure 4.3: Adapted Enjoy scale mean comparison of static and interactive maps.



For further understanding, Figure 4.5 shows the adapted ENJOY scale scores for each subdimension. The maximum score for each subdimension is 15. The pleasure, relatedness, competence, and engagement scores of the interactive map were higher than static map. The only challenge/ improvement of the subdimension reaches a similar score of 10.36. With also implemented the Shapiro-Wilk test to inspect the normality, the result showed that all subdimension scores were normally distributed. With the paired t-test, only two subdimensions, relatedness and competence, showed significant differences between the static map and the interactive map, with p-values of 0.026 and 0.032 in order. The subdimensions' normal distribution graphs can be found in Appendix A.1.

Figure 4.4: Data distribution of mean adapted ENJOY scale scores.

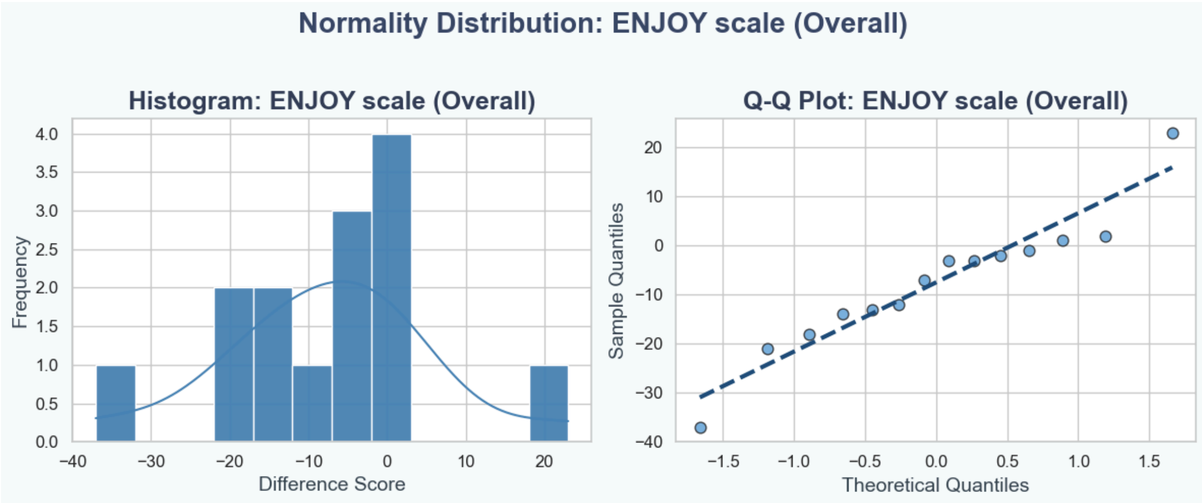
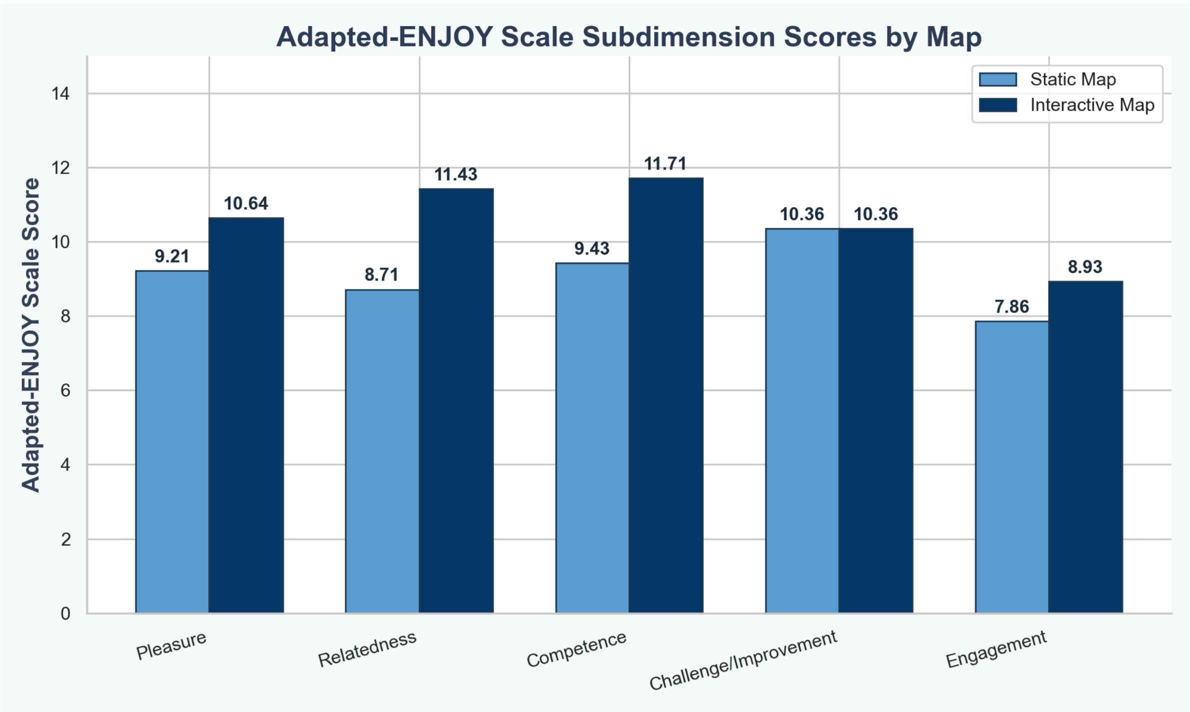


Figure 4.5: Adapted ENJOY scale for each subdimension mean scores between the static and interactive maps.



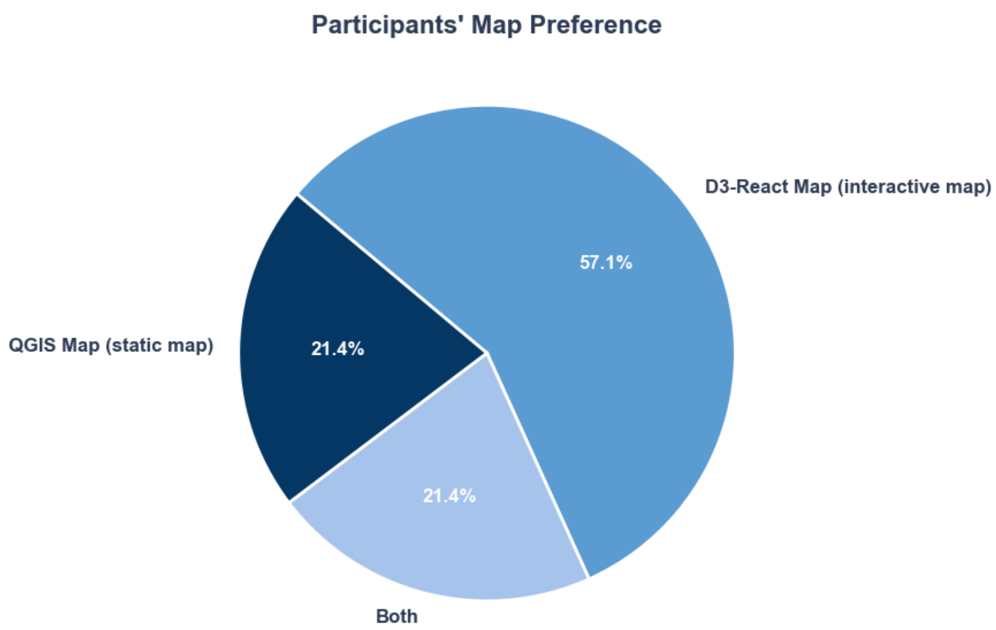
4.3. Subjective general questions

4.3.1. Map preference

To understand which map presents a better experience during the experiment, the participant has been asked about their map preference. The result showed that 57.1% of the participants were more likely to prefer the interactive map, 21.4% answered the opposite, and 21.4% stated that both maps were similar (Figure 4.6).

The participants who were most likely to use the interactive maps stated that the interactive map allows them to explore data more than the static map. Also, the features such as filtering and brushing extension on the histogram allowed the participants to find more details regarding the data. For example, the interactive map could present the route of the train and bus at the same time, and also it could be chosen to only one specific route. The brushing extension also allows the participant to understand the data more accurately by slicing the square to find the pattern between the days of commuting time. The adjustment hexagonal size also helps the participant make the data integration easier.

Figure 4.6: Map preference by participants.



On the other hand, some participants prefer the static map. Since the static map directly presented four images at the same time, comparing the images was easier than clicking every time to gain the information. The other reason was that the interactive map was not working well due to the loading time. The participants needed to wait, and there was no response after several clicks.

Other participants chose both maps were also gave their reason. One participant felt that the static map showed everything at the same time, even though it consumed more space on the screen. On the other hand, the interactive map consumes less screen space; however, it needs more interaction to find specific information. Another participant only stated that the interactive map could present the data with more granularity, but was less responsive due to the loading time. The rest did not give a specific reason.

4.3.2. Subjective experience with the static map

According to the participants, the static map had some advantages. The static outperformed especially to capture the data in general. There was no additional interaction and more focus on finding the information regarding the task since it was already presented in one figure. The static map also loads quickly on the browser without waiting time due to the loading time.

In contrast, some disadvantages of the static map, according to the participants. There was no possibility to explore, identifying specific routes or temporal relations, combining the variety of the parameters, and less details of the information of the study. Also, the static map needs more space to present all images at once, too many variables, is hard to interpret, has complicated information, and takes more time to learn the map.

In summary, the participants felt the static map was boring, less interactive, and not possible to explore the data in detail, even though the static map was good for understanding the data in general, and no waiting time during rendering

4.3.3. Subjective experience with the interactive map

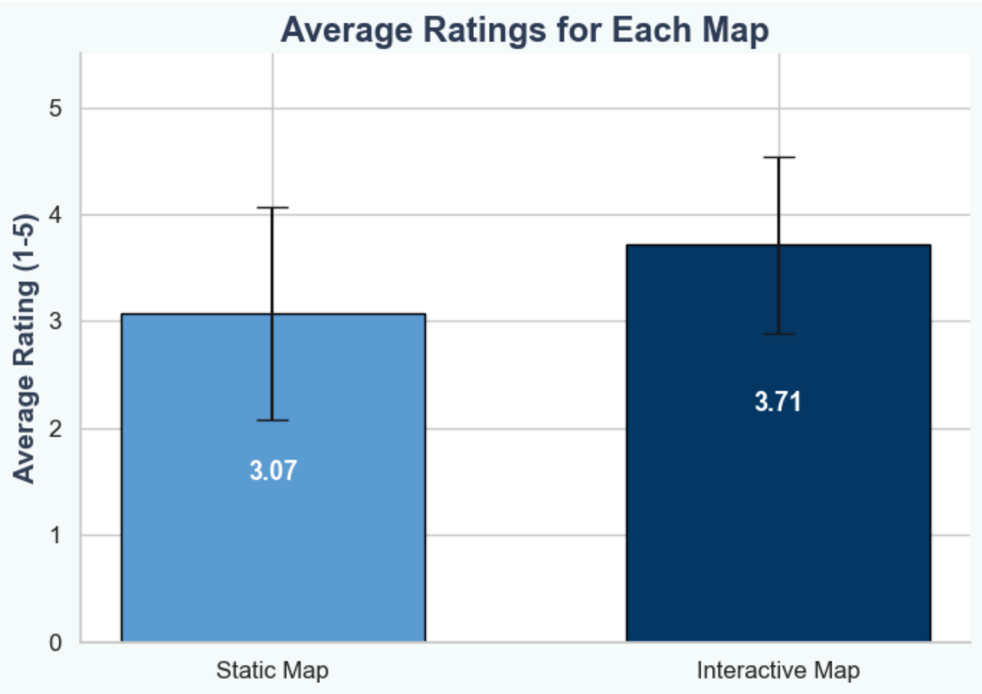
The advantages of the interactive map were the ability to explore more information since it had interactive menus. It allowed the participants to find different combinations, find specific information, and focus on the specific variables. The brushing option also gave the possibility to find specific information for certain days.

The most familiar of the disadvantages of the interactive map among participants was the rendering time. The participants had an issue while changing the option on the filters menu of the slicing brushing tools, which took a longer time.

In summary, even though the interactive map did not work properly due to the rendering time and made the browser work harder, most of the participants enjoyed using the interactive map. The ability to explore the data interactively and have fun was well mentioned by the participants during work with the interactive map. Figure 4.7 shows the average rating of the static and interactive maps from the participants. With the scale ranging from one to five, it is clear that the interactive map achieved a higher point, with 3.71 points compared to the static map with 3.07 points

The original and complete answer in this section can be found in the appendix..

Figure 4.7: Average rating between the static and interactive maps.



Chapter V
Discussion

The present study examined static and interactive maps with hexagonal shapes, which involved 14 participants. Since the within-participants experimental design was used, all participants had a similar experience and treatment. The two main variables in this study were accuracy and the user experience. This chapter focuses on the discussion based on the experimental results

5.1. RQ 1: Is there a significant difference in accuracy between the static and interactive maps?

The experimental result showed that there was no significant difference between static and interactive maps in accuracy. Although the static map had a slightly higher score than the interactive map, the gap score was less than 0.5. Both maps were designed with similar shapes and color scale to present similar nuances. According to Sanyal et al. (2009), color maps were an important aspect in visualizations and yielded the highest accuracy for spatial detection.

The static and interactive maps could achieve almost a similar score in accuracy to portray the data sets through the visualization. With the variation of the density among the maps, the question regarding this aspect is also assessed, for comparison, which area had a higher or lower score that corresponds with darker and lighter colours. Zhu (2007) defined accuracy as the degree to which visual encodings align with the actual data structure and including cognitive fidelity, which meant how well visualization supports correct mental representation of the data.

Therefore, the proposed interactive map that was developed with D3.js and React could produce approximately the same result in accuracy as QGIS software regarding presenting the data visualization within a hexagonal shape.

5.2. RQ 2: Do the static and interactive maps lead to significantly different user experiences?

The user experience is investigated through the adapted ENJOY scale as overall and each of its five subdimensions. The overall adapted ENJOY scale's score showed that there was no significant difference between the interactive and static maps. However, the interactive map had a slightly higher score compared to the static map.

In addition, the adapted ENJOY scale subdimensions also showed that the interactive maps outperformed static maps, especially in four of five subdimensions: pleasure, relatedness, competence, and engagement. Moreover, the relatedness and competence showed significant differences between the maps. Only the subdimension challenge/ improvement had a similar score among the maps. The open questions also showed that the majority of the participants preferred the interactive map to the static map.

According to Davidson et al. (2023), the relatedness subdimension measured the feeling of connecting with the visualization, appreciating the layout and design, and the confidence to share the information with others. In addition, the competence was the feeling of the ability to use, explain, and analyze the data visualization. According to the participants, the interactive map allows them to explore the map to find deeper information. The filter features also give the freedom to find information with the combination of a variety of data parameters. On the other hand, the static map can only present one information with one figure; as a consequence, it would take more space on the monitor to show all the relevant information from the data. The histogram with the brushing feature also helped the participants to investigate the data distribution for specific days that are not possible to be implemented in the static map.

Even though the static map was less interesting, it was more beneficial to portray the data in general compared to the interactive map. In addition, the static map is also faster and lighter when rendering compared to the interactive map, which consumes more time waiting during the experiment. However, creating a figure of the static map in QGIS software also took five to ten minutes for rendering with similar data points, which can be calculated in less than one minute in the interactive map.

This study showed the in-line result from the previous studies. The static map was a fixed narrative and oversimplified complex data and limiting the ability of the user to explore underlying questions (Rodríguez et al., 2015; Cook et al, 2016). According to them, the interactive map enables free exploration, allowing users to manipulate data and discover hidden relationships that were not visible in the static map.

In summary, the vast majority of the participants agree that the interactive map presented the data visualization better than the static map. Both static and interactive maps have their advantages and disadvantages. The static map, which was created by QGIS software, had a better score in accuracy, was more effective in portraying the data in general, and took less time for rendering, even though this map lacked interactivity, was not possible to explore, and took up more space on the screen monitor. In contrast, the interactive map, which was developed with D3 and a React application, had some interactive features such as a filter menu and a histogram with brushing, which were very functional to explore the data, even with specific days and a variety of variable combinations. However, the rendering time was the most complained about by the participants.

5.3. Implications and limitations

This study found that the interactive map with the hexagonal bin allows participants to explore the data more specifically with the filter combination of the parameters in different variations. With the hexagonal shape, the overlapping data points could be avoided compared to the circle map. In other words, the proposed map can be a guideline to develop more advanced interactive data visualization with the hexagonal map, especially when dealing with complex and huge spatiotemporal datasets.

However, some limitations of this proposed map are especially to optimize the render time. This map is manually calculated by the value inside the hexagon shape once the filter is applied or by sliding the brush features. The author has not yet found how to calculate the datapoints faster every time the filter and brush features are changed. Also, the zooming option was not available on this map. The future research needs to find how to integrate the editable map of the world, such as OpenStreetMap (OSM), to enable the zoom ability and adaptability to recalculate and adjust the hexagonal shape based on the value of the data points.

Chapter VI
Conclusion

This present study proposes a data visualization regarding spatiotemporal data of travel experience with public transport as an interactive hexagonal map. The hexagonal shape has been chosen to avoid the overlapping of the data points that mostly occur when using dot or circle maps. As a comparison, the hexagonal static map created with QGIS software was used.

The QGIS software is an open-source application that is commonly used in geovisualization. By comparing the accuracy of these maps, it can be a good predictor to evaluate the accuracy of the interactive map. In addition, the static map by QGIS only portrays the visualization as a figure without the ability to explore and combine different parameters in one interface. Therefore, the interactive map was developed with interactive features such as a filter and a histogram with brush extension to allow participants to investigate the data in more detail and specifically.

As a result, the static map by QGIS had a slightly higher score in accuracy compared to the interactive even though statistically there is no difference. It can be assumed that the interactive tool developed with D3 and React in this study could present data that was nearly identical to open-source QGIS software in accuracy.

In addition, the participants' experience also showed that the adapted ENJOY scale in the interactive map outperformed the static map. Four out of five of its subdimensions' scores also represented the high score among the interactive map, with only one subdimension obtaining a similar score. Moreover, the relatedness and competence subdimensions' scores indicated a statistically significant difference.

The majority of the participants prefer and agree that the interactive map was more interesting than the static map. The common reasons were that the interactive map could present the data more variably by combining several parameters in the filters, which was not possible to apply these features in the static map. However, the interactive map was taking more time to render and load the map, especially when including “all participants” data. This was the common complaint by the participants in this experimental study.

In conclusion, the interactive map in this study showed positive outcomes not only in terms of accuracy but also in user experience. However, it needs to be evaluated, especially regarding how to minimize the rendering time and optimize its accuracy. In addition, this proposed map has the potential to be developed in advance and applied in further studies, particularly when utilizing large and complex spatiotemporal data.

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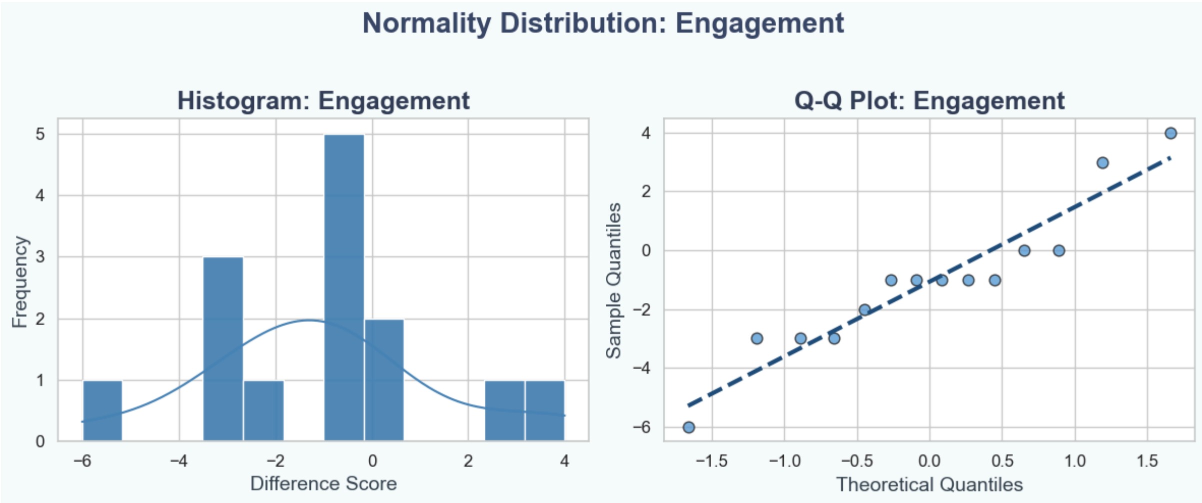
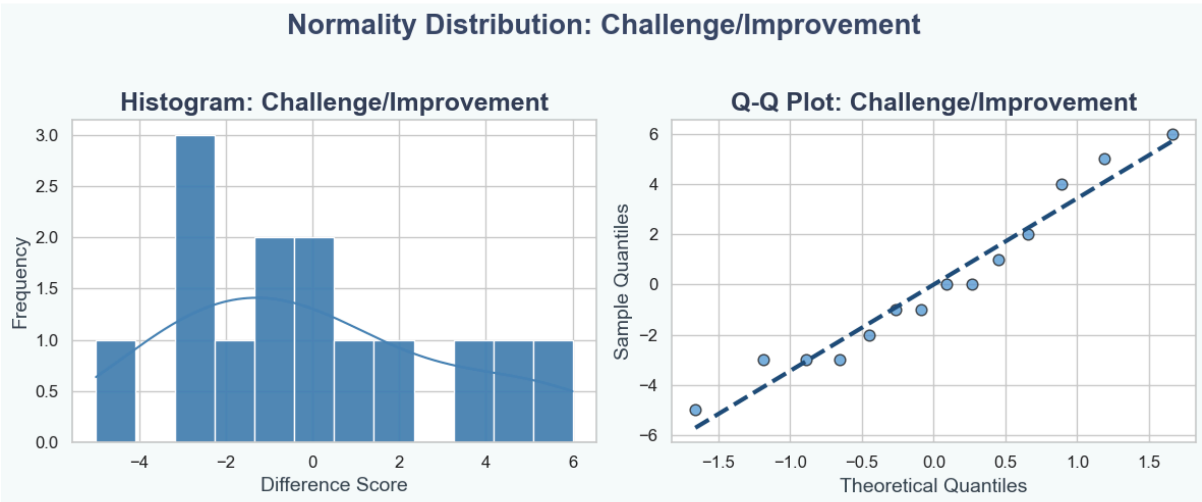
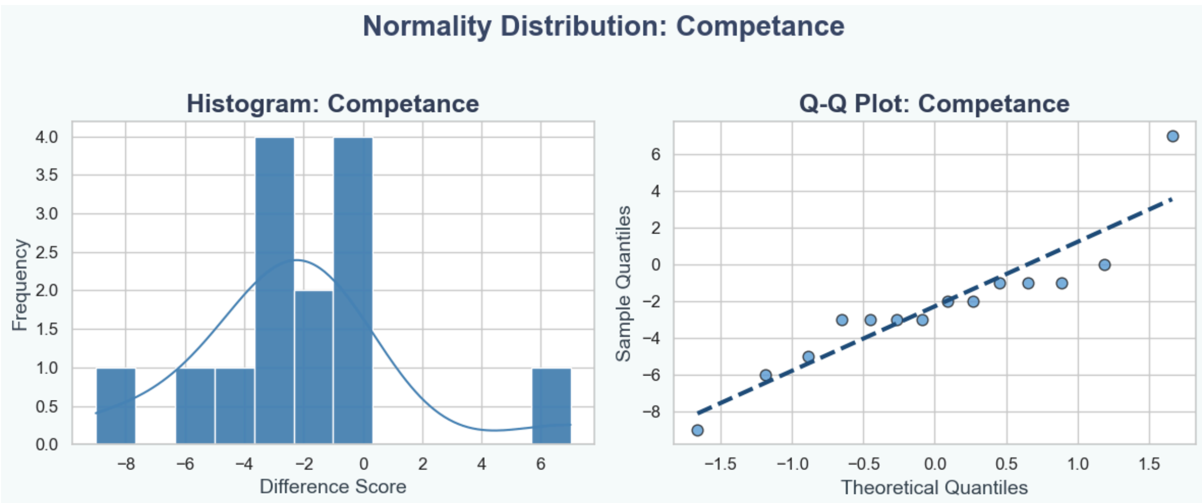
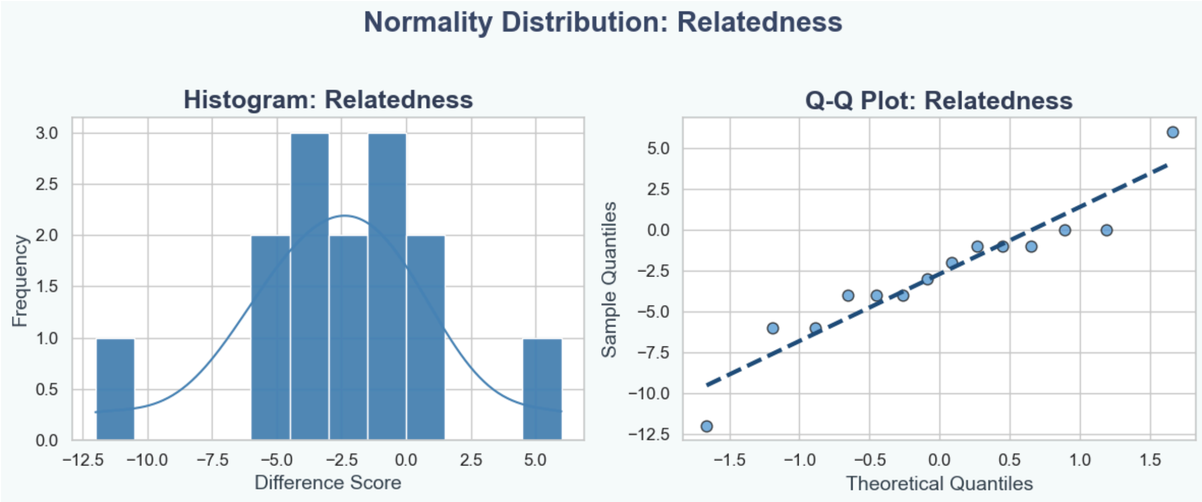
Appendix

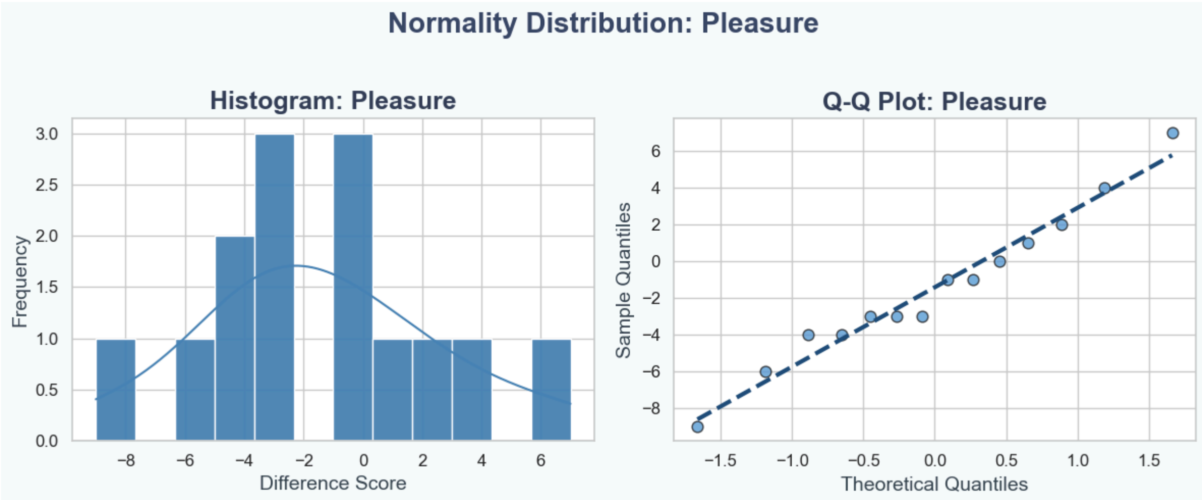
A. The normal distribution graphs adapted ENJOY scale subdimension








Normality Distribution: Relatedness
Histogram: Relatedness
Frequency
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−12.5
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
Difference Score
Q-Q Plot: Relatedness
Sample Quantiles
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
−12.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
Theoretical Quantiles


Normality Distribution: Pleasure
Histogram: Pleasure
Frequency
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−8
−6
−4
−2
0
2
4
6
Difference Score
Q-Q Plot: Pleasure
Sample Quantiles
6
4
2
0
−2
−4
−6
−8
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
Theoretical Quantiles

B. Original answer for subjective general questions.

B.1. Which data visualization do you like the most? Can you elaborate on your answer?

Participant	Which map do you like the most	Elaborate answer
1	D3-React Map (interactive map)	More exploration possibilities, more details
2	Both	Interactive map allowed for more granularity but it did not run well on my computer, especially when all participants were selected. I was struggling at first to identify the "brush" element.
3	D3-React Map (interactive map)	D3 Filters work good, but the website is too slow. But i like the concept
4	QGIS Map (static map)	I could focus on comparing the images, then to click every time I need the info.
5	D3-React Map (interactive map)	I liked the option of increasing the hex. sizes, it made the integration easier.
6	Both	it depends on the context: the static map consumes more screen area but "everything is there", whilst the interactive map uses less area but to find a specific info, interaction is needed. But I like the static better, if I have to choose.
7	Both	No, there is no specific reason
8	QGIS Map (static map)	the d-3 interface wasnt working well. it needed several clicks and didnt respond well to my cursor.
9	QGIS Map (static map)	Immeadiatly had an overview of all the data. No need to arrange and wait for the interactive map
10	D3-React Map (interactive map)	Interactive map needs less effort, the information is just there for you, almost already fully interpreted.
11	D3-React Map (interactive map)	the D3-React Map enables me to slice and dice the data through the filters, making it easier to understand and further analyze the data.
12	D3-React Map (interactive map)	D3-React Map give more opportunity to explore the data and the filter option help to give the specific data as needed.
13	D3-React Map (interactive map)	More precise with values and it distinct the bus and train group, easier for the reader to use, analyze and interpret the data.
14	D3-React Map (interactive map)	The interactive map allows you to easily visually compare different states of a map with different parameters applied, unlike static QGIS Map

B.2. From your subjective experience, what are the advantages and disadvantages of using QGIS map (the static map)?

Participant	Advantages and disadvantages of using QGIS (the static map
1	disadvantage: static, no possibilty to explore
2	GOOD: Quick overview over a location as a whole, can easily be shared - BAD: Identifying specific routes or temporal relations without option to deselect some other information is difficult or impossible
3	static advantages: speed of display
4	Disadvantages: it provides less info in one study, it needs more space to present all images once. Advantages: it brings more focus for the users, to find alternatives to fix the problems described.
5	adv.: loads faster, doesn't lag; dis: hard to interpret, too many variables displayed at once
6	Advantages: "everything is there", "can choose directly which diagram for HRV or stress level". Disadvantages: the maps' legend is more complicated as there are more items to explain. Also, takes more time to learn the map but once used to it, it's faster to find info.
7	you can see directly what you should focus on but it´s not so flexible than the other map
8	all the visualisations are in one page making it easier to compare and contrast
9	+: better overview of general data easy, no need to arrange something no wait time -: less details less categorization in sub groups
10	The static map has all the information there, there is no chance of some interface error/no need for good operating RAM.
11	Advantages: quite lightweight on my browser Disadvantages: it wasn't really straightforward and difficult to distinct the mode (train, bus) from the map; it wasn't possible to look into the details of the data
12	Advantages: easy to capture general info. Disadvantages: confusing if you need to compare specific data.
13	Static map is only good to see the overall or general results of the data. I can only sense the average and very high-level interpretation from this static map.
14	Resistance to changes in variety of parameters and their combinations

B.3. From your subjective experience, what are the advantages and disadvantages of using D3 map (the interactive map)?

Participant	Advantages and disadvantages of using QGIS (the static map
1	advantage: possibilites for exploration, interactive menu, change of bin size, mode choice disadvantage (in general, not compared to GIS): mode values appear incorrect
2	GOOD: Toggling of specific data you don't care about means you can ask more specific questions to the data, specifically as it relates to certain routes or certain days - BAD: The performance is very bad, it takes a long time to load and it does not feel very responsive on my computer, it would probably be better to do more of the calculations at the start and not during runtime.
3	D3 disadvantages: filtering for mode (bus train) is not clear
4	Disadvantages: took time to click and compare. Advantage: good enough to filter infos or describe a situation
5	adv.: can choose the variable to focus on, can change the size of the map; dis: took a bit of time to load
6	Advantages: it's interactive, so more fun to use. Disadvantages: it's interactive, so to find a specific info, needs to make some adjustments to the map.
7	i think you can see many different combinations of the many parameter but if there are too many it could be too much and it would be hard too focus on the important things
8	slow response, need to switch between different modes
9	+: Way more details and sub groups Better and deeper analysis -: Annoying to wait for rendering Not as good for a fast overview
10	It's easier to comprehend, as the data is fragmentated.
11	Advantages: easy to look the data into more details, easy to distinct between modes and the metrics Disadvantages: it was slow on my browser, took a while until the data was fully loaded after selected a value from the filters
12	Advantages: easy to use and to get specific data. Disadvantages: the app a bit slow to open, need a lot of computer resource.
13	More accurate and if there's any certain purpose or category to look at or to analyze, interactive map bring more advantages than static map. More precise information can be derived from the interactive map.
14	The advantage in its plasticity and flexibility to various combinations of parameters applied simultaneously; the disadvantage in the execution speed and power resources needed

B.4. From your subjective experience, how do you describe your feelings of using the static map and interactive map?

Participant	Feelings of using the static map	Feelings of using interactive map
1	boring	interesting
2	It's fine. If you to get a quick overview then use this. Works especially well if we can see clear structures in locality.	Customization is nice and engaging. If I was interested in toggling specific routes/participants/days, I would use this approach
3	i need more labels (text) for clarification on the pictures	i would prefer that the filters are not immediately applied, i would rather have a "apply filter" button. Changing multiple filters consecutively takes too much time.
4	more familiar, easier to analyze the data, support more on decision making process	too mechanical, provide more data needed, more flexible to choose infos
5	took some more effort to understand so I was a bit overwhelmed	was easier to navigate, and maybe because I already knew the topic/questions after I knew what to look for, so it was less overwhelming
6	the instructions can be done better, about the left/right indication and coloring indexes.	maybe would be good to have an indicator of whether the map is being loaded or is already functional.
7	i thinks it was very interesting	it was interesting, I never worked with something like this I think
8	easy	impatient
9	simple and fast data	slow but more detailed
10	Tiring, like homework.	More fun, almost like a game.
11	quite difficult to make sense which one the data for bus and for train	I directly went to the filters, see what I can do with them; however it was very slow and took a while until the data was loaded.
12	Not happy. Overwhelming when need to compare the data.	Excited and enjoy to explore the map.
13	A little bit confuse as I can't pin point the values, so when answering questions I was just thinking common sense/average in my mind. Didn't even calculate the numbers as it wasn't clear.	Easier, clear, Average value is shown already, definitely more time efficient in case looking for data from the interactive map.
14	Confusing, close attention demanding	Convenient, easily understandable

B.5. From 1 to 5, what is your rating of the static and interactive map?

Participant	Rating of the static map	Rating of the interactive map
1	2	4
2	3	4
3	3	4
4	4	3
5	2	3
6	4	3
7	3	4
8	5	2
9	4	3
10	3	4
11	2	4
12	2	4
13	4	5
14	2	5

B.6. What is your suggestion that can be improved in presenting the data visualization in this experiment?

Participant	Presenting data visualization
1	It would be really cool, to link the data not only to the mode, but also to train lines etc. I missed walking as mode
2	If your data is bound to specific trips or modes of transport, connecting them via line plots to highlight where people move would help a lot.
3	more labels
4	in one question, there was a phrase with -more less satisfied- the meaning was not accurate/double meaning : more or less?
5	nothing I can think of
6	a back button or extra explanations on what the numbers mean (white or red HRV)
7	maybe in the D3-React i would prefer a bit less things you can change for example maybe just three ages like from 18 to 30 and so on, it would have been easier or maybe you can show like 3 maps at the same time and one would show the train situation, one bus und the other the tram that the person who will work with it can just change maybe the gender of the persons who were a part of the experiment and it shows it on all 3 maps, in my opinion it would be easier to see the differences.
8	make the d-3 interface more responsive
9	Render time for interactive map is annoying
10	Maybe bigger maps, bigger interactive objects, as it was sometimes hard for me to fully see what was going on. And my computer struggled with the interactive map.
11	- optimize the code so it loads faster - add a loading screen before the data loads - add some tooltips/description on what do the metrics mean
12	The data visualization in D3-React already helpful.
13	At first, it was a bit confusing on static map, which route is actually for bus and train. Perhaps would be good to show example on which route you are talking about from the static map for bus and train.
14	efficiency in execution of the interactive map (my notebook was extremely slow in interaction with the map)

B.7. In general, what can be improved in this experimental setting, and from 1 to 5, what is your rating?

Participant	Improvement of the experimental setting	Rating of the experimental setting
1	some questions were a bit ambiguos (asking for two things in one question) Questions should be asked while exploring, not after	3
2	-	5
3		3
4	if it is possible to put the 2nd questionnaire, on the same page with the 1 questionnaire. Not in another link tab. The general description about the study was too much, should be described with less sentences.	2
5		4
6		4
7		4
8		4
9		4
10	I was confused about "left side of your monitor is for trains".. at first I thought that two maps on the left were presenting something different from two maps on the right.	4
11	maybe use a scenario-based experiment, ask the participants to do a task, and see how they perform in both visualizations	3
12	N/A	3
13	I think instruction was very clear. It can be daunting to read rather technical instructions with some jargons, but in the end it was clear. Good thing is that while filling out questionnaire I can still also check the map to see whether my interpretation is correct/if I answer the question correctly based on my observation on the map.	5
14		5