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Identifying the factors that improve user adaptation of AI-generated routes

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Abstract

The rapid innovations of artificial intelligence (AI) in navigation systems have revolutionized route generation, yet research into the factors that influence user adaptation remains limited. This study aims to bridge this gap by exploring key factors that impact drivers' willingness to follow AI-generated routes. A survey was designed and distributed that examined the following five formulated factors: number of traffic lights, number of roundabouts, distance on highway, number of gas/charging stations, and distance of a scenic route. The results were then processed using the Bradley-Terry model and bootstrap resampling method. These analyses identified that stoplights and roundabouts were avoided, while highways, stations, and scenic routes were preferred in relation to travel time. Notably, it was also found that drivers of electric cars were significantly more influenced by the availability of stations than those driving petrol vehicles. These findings provide insights into the human-AI interaction in navigation. It also underlines the importance of incorporating these factors and personalisation into the design of future AI navigation systems to enhance user adaptation.

Content

1. Introduction

Artificial intelligence (AI) has become a cornerstone of the modern-day navigation, generating routes and optimising them based on real-time information. Both in the professional context as well as the private setting it has become essential in guiding individuals to their destinations efficiently (Dikshit, 2023). Reliance on AI-generated routes has only increased with advancements in technology, and this trend is only expected to continue as algorithms improve further. Therefore, the factors considered by AI in generating these routes are vital to ensuring that they are both optimal and beneficial for the user (Zhang, 2023).

Previous studies aim to identify the factors that influence the trustworthiness of AI in general to better understand what motivates people to adopt these technologies (Choung, 2022). Additionally, methods have been developed to improve cooperation between AI and humans (Ramchurn, 2021). With regard to AI routing specifically, existing research focuses predominantly on the technological perspective and the possible risks of over-reliance on these navigation systems (Cummings, 2004). On the contrary, the research on the human perspective and desires is limited. This study aims to expand the understanding of users of these systems to improve the way routes are generated. The insights gained could be utilised to incorporate the user experience more effectively into the algorithms. This leads to the following research question:

How can AI-generated routes be improved to better adapt to user needs?

The thesis will address this question by first formulating the various factors that potentially influence the suitability of routes. Subsequently, a survey will be conducted to assess the effects of each factor. Finally, the results will be analysed using the Bradley-Terry model and bootstrapping method to determine the effect of the different factors on users' willingness to adopt the generated routes.

2. Related work

2.1 Adaptation and trustworthiness of AI

As AI emerges as a new technology, the interaction between humans and AI is increasingly being studied. Zhao et al. (2022) examined the importance of adaptation in human-AI cooperation, emphasising how AI systems that can adapt to humans produce more effective collaborations. This is supported by Endsley et al. (2021), who highlighted that ability of AI to dynamically adjust its support contributes to an increase in confidence and trust. It is crucial to explore the broader aspects that contribute to trust in AI systems, as it inherently tied to the perceived adaptability of AI technology.

Trust is a cornerstone of humanity's relationship with AI, according to Siau & Wang (2018) and Choung et al. (2022). The acceptance and progression of AI technologies depends on the confidence of users. Systems that are perceived to be more trustworthy are utilized more. Therefore, trust is generally seen as a beneficial attribute and key component to incorporate in AI systems (Reinhardt, 2023). However, trust is not static and continuously develops through ongoing developments and interactions (Choung, 2022; Endsley, 2021). Consequently, research on the trustworthiness of AI has been conducted focusing on the elements that influence the trust and adaptation. From these studies, a comprehensive set of attributes is identified that shape the user's trust in AI technologies more broadly.

One significant component that influences trust is the ethical and fair behaviour of AI systems (Endsley, 2021; Zhao, 2022). Trustworthiness in AI is closely associated with several ethical principles and understanding them provides a foundation for examining factors that shape user trust. Fairness is paramount in this; a fair AI system avoids biases and ensures equitable treatment of all users to prevent inequalities. Accountability is another factor an ethical AI system should adhere to, ensuring liability is clearly defined, if any issues should arise. Issues and harm in general should be prevented to build and maintain trust in AI (Reinhardt, 2023).

Transparency in AI systems is another important factor in the acceptance of these systems, closely associated with the concept of ethical AI (Choung, 2022; Reinhardt, 2023; Siau, 2018). Users tend to prefer AI systems that can explain their actions and the rationale behind their decisions (Turmunkh, 2022). The ability of an AI system to provide understandable and clear explanations for its decisions enhances users' feelings of being informed and confident, resulting in increased trust.

However, these factors alone are not sufficient. Human involvement in AI processes also improves user perception. The human Favouritism Rationale, as described by Inie (2024), argues that AI systems that incorporate human input will show more human like characterises or more human centric benefits which results in preference for these systems by users (Vogels, 2023). Consequently, AI technology should be designed from the perspective of the end user. This involvement can be in a variety of stages ranging from the initial programming phase to the continuous monitoring and interaction (Okamura & Yamada, 2020). Additionally, the design of the interface plays a vital role in fostering trust. Research suggests that the trust of a system is enhanced by an intuitive and user-friendly interface, making it more approachable for users (Lee, 2004). Effective design should prioritize clarity and usability to improve the satisfaction. In car navigation the relevant factors would be important to display for instance.

Moreover, the research has demonstrated that consistent and reliable performance of AI systems is key to sustaining trust. Users are more likely to trust systems that perform well under varying conditions and consistently meet their expectations (Choung, 2022; Siau, 2018). Reliability ensures that users can depend on the system, which is particularly important in applications such as car navigation where accuracy and consistency are critical.

2.2 The technological aspect of AI routing adaptation

Studies on AI routing often emphasise the technological aspects beyond mere reliability. Dikshit et al. (2023) explored how AI can enhance transportation efficiency by incorporating vast amounts of real data into route generating algorithms. The system has a comprehensive view of the traffic conditions by integrating data from various sources including GPS devices, traffic cameras, and sensors. The real data can also be utilised to predict and avoid future bottlenecks, further enhancing the user experience.

Real-time data, similarly, plays an essential role in dynamic route adjustment through the Road Condition Monitoring (RCM) (Ranyal, 2022). RCM focuses on analysing the status of the road infrastructure as it is affected by heavy traffic, harsh weather conditions, aging, poor construction quality, and lack of appropriate maintenance. By processing data of multiple sources, including drones, the system can optimize travel paths. This not only leads to more efficient and safer routes for the end-user but also contributes to reduced carbon emissions.

The optimization and safety improvements brought by real-time data are directly tied to the overall user experience, which is vital for the adaptation of AI-generated routes. Based on the Technology Acceptance Model (TAM), Ge (2023) identified perceived usefulness (PU) and perceived ease of use (PEOU), in addition to trust, as significant predictors of user's intentions to utilize AI navigations systems. Effective experience design can enhance these crucial factors to influence the users' attitudes positively (Lee, 2004). Therefore, a user-friendly interface should be designed to cater to the PU and PEOU, showing relevant factors to the user.

Zhang et al. (Zhang, 2023) outlined a framework that incorporates the previously mentioned real-time traffic data, road conditions, and user preferences into dynamically generated routes. The case study in this paper demonstrates how this framework reduces travel time and improves user satisfaction by providing adaptive and personalized AI routing solutions. This shows the importance of understanding these factors to create a reliable and user-centric navigation system.

These navigation systems are still prone to errors however, as it can overlook factors or miscalculated values. This introduces the risk of over-reliance, where a human user disregards other information fully trusting the automated output of the system. The human tendency to rely on automated computer-generated solutions is known as automation bias and should be kept in mind during the designing process. These risks can be addressed by supporting user situational awareness and encouraging active monitoring and critical assessment (Cummings, 2004; Okamura & Yamada, 2020).

2.3 Perspective of the end-user

The development of AI navigation systems thus has increasingly focused on the perspective of the user to responsibly enhance trust. The study by Wang et al. (Wang, 2022) provides the Driver Preference-Based Route Planning (DPRP) Model for achieving this objective. This system collects drivers' preferences and utilizes them to recommend optimal routes. Various attributes were considered in the study. There were divided into attributes that had a positive effect:

- Scenery
- Radius of curvature
- Number of Lanes
- Lane width

And attributes that had a negative effect:

- Distance
- Congestion
- Traffic flow number of pedestrians and bicycles
- Congestion rate
- Separation of motor vehicles and non-motor vehicles
- Cost of time
- Fuel consumption
- Toll fee
- Number of traffic lights
- Intersections
- Turns

The preferences are collected from big data and direct driver input, allowing the system to assign a weight to each attribute. Then a “road resistance” value is calculated from which the routes with the lowest value are recommended to the user. By employing this method, the DPRP model is able to provide route suggestions that are both personalised and efficient.

The factors that should be considered and the extent of their influence is further researched by Amirgholy et al. (Amirgholy, 2017), looking into similar factors as used in the DPRP model. The study used a survey too to determine the impact of each factor, asking the participants to rank the importance of each attribute. A distinction was made between weekdays and weekends. First, the study discovered that the different variables do not correlate, thus they can be seen independent from each other. Scenic quality was found to be more significant on weekends, while the travel time and the cost of the trip was more important on weekdays. Additionally, the road safety was consistently ranked as important. Amirgholy et al. (2017) showed, in a different part of the survey, that 27% of participants chose other routes than the one the AI navigation system suggested, highlighting the need to understand user' preferences.

There also factors that originate from the user that impact the adaptation of AI route recommendations. Samson et al. (2019) identify several of these factors:

- Practicality and sensibility were found to be the most influential one, being considered 94.12% of the time by users.
- Familiarity with the recommended routes were taken into account 86,15% of the time.
- Suitability of the road concerning safety only influenced the decision of the user 26,80% of the time.
- Drivers also use social networking sites and their community to seek information that is not provided by car navigation.
- The urgency of the trip is another factor identified that influences the user's choice to follow the recommended route generated by AI.

Consequently, the paper suggests context aware recommendations to ensure that the navigation aligns with the driver and his or her needs.

2.4 The relevance of this study

As described earlier, there are numerous attributes influencing the decision of a user to choose a route. This results in users not following the path with shortest travel time in 60% of cases according to a study by Zhu and Levinson (2015). The study further underlines that more research is needed into the factors that have an impact on user adaptation. This study aims to expand that knowledge, adding to the understanding of these factors. Eventually, this could lead to greater consideration of attributes in the design process of AI systems that generate routes, resulting in increased user adaptation.

The importance of the adaptation of AI routing is furthered emphasized by van Rooijen et al. (2008), who examined the impact of navigation systems on traffic safety in the Netherlands. Combining results from a literature survey, database analysis, user survey, and instrumented vehicle, they found that navigation systems reduce driving errors and improve navigational efficiency. This conclusion is supported by evidence of improved driving behaviour, reduced stress, and a decrease in both the number and cost of damage claims.

3. Hypotheses

3.1 Determining factors and the associated hypotheses

Firstly, the research process starts with determining the possible factors that influence the Adaptation of AI-generated routes. Building on the related work discussed earlier, the research identifies the following five factors to investigate, each accompanied by a hypothesis. The hypotheses all have a null hypothesis to be able to test if they are statistically significant; how this is determined is explained further in section 4.4.

1. **Number of stoplights**: In the Driver Preference-Based Route Planning (DPRP) Model by Wang et al. (2022), it is shown that the number of stoplights negatively impact the user preference for a route. This is crucial to investigate further as traffic lights are profoundly found on routes, in particular in urban areas. Therefore, the hypothesis is as follows:
    - Null hypothesis (**H0**): The number of stoplights does not influence the user's willingness to adapt the route.
    - Alternative hypothesis (**H1**): The number of stoplights influences the user's willingness to adapt the route.
    - For this hypothesis the following conditions apply:
        - 20 min ≤ Time ≤ 32 min
        - 30 km ≤ Distance ≤ 50 km
        - 0 ≤ Stoplights ≤ 8
        - 0 ≤ Roundabouts ≤ 8
        - 0 km ≤ Scenic route ≤ 12 km
2. **Number of roundabouts**: Wang et al. (2022) mentioned intersections and turns as negative factor, indicating roundabouts could be of also of negative impact. However, the study on the impact of roundabouts is minimal, while the number of roundabouts is only increasing due to their improvement of safety at intersections (Dijkstra, 2014; Lazo, 2022). This highlights the importance of testing this factor in user adaptation, leading to the following hypothesis:

- Null hypothesis (**H0**): The number of roundabouts does not influence the user's willingness to adapt the route.
- Alternative hypothesis (**H1**): The number of roundabouts influences the user's willingness to adapt the route.
- For this hypothesis the following conditions apply:
  - 20 min ≤ Time ≤ 32 min
  - 30 km ≤ Distance ≤ 50 km
  - 0 ≤ Stoplights ≤ 8
  - 0 ≤ Roundabouts ≤ 8
  - 0 km ≤ Scenic route ≤ 12 km

3. **Distance on highway**: The influence of the distance of highway on the choice of individual to opt for a specific route is limited. However, highways are an integral part of covering long distances by car. Therefore, the third hypothesis is formulated as follows:
   - Null hypothesis (**H0**): The distance of highway does not influence the user's willingness to adapt the route.
   - Alternative hypothesis (**H1**): The distance of highway influences the user's willingness to adapt the route.
   - For this hypothesis the following conditions apply:
     - 3 hours 30 min ≤ Time ≤ 4 hours
     - 300 km ≤ Distance ≤ 400 km
     - 50 km ≤ Highway ≤ 250 km
     - 4 ≤ Stations ≤ 20
     - 0 km ≤ Scenic route ≤ 120 km
4. **Number of gas / charging stations**: The number of stations could have become a more influential factor on users as electric car drivers are more concerned with vehicle's range (Franke, 2013). Consequently, this motivates to consider the following hypothesis:
   - Null hypothesis (**H0**): The number of gas / petrol stations does not influence the user's willingness to adapt the route.
   - Alternative hypothesis (**H1**): The number of gas / petrol stations influences the user's willingness to adapt the route.
   - For this hypothesis the following conditions apply:
     - 3 hours 30 min ≤ Time ≤ 4 hours
     - 300 km ≤ Distance ≤ 400 km
     - 50 km ≤ Highway ≤ 250 km

        ▪ 4 ≤ Stations ≤ 20
        ▪ 0 km ≤ Scenic route ≤ 120 km

5. **The distance of a scenic route**: Scenic views have positive influence on route selection, as highlighted by Amirgholy et al. (2017), being valued for the aesthetic value. To further investigate how the desire for scenic routes influences the choice of routes the following hypothesis is formulated:
    - Null hypothesis (**H0**): The distance of scenic views does not influence the user's willingness to adapt the route.
    - Alternative hypothesis (**H1**): The distance of scenic views influences the user's willingness to adapt the route.
    - For this hypothesis the following conditions apply:
        - 3 hours 30 min ≤ Time ≤ 4 hours
        - 300 km ≤ Distance ≤ 400 km
        - 50 km ≤ Highway ≤ 250 km
        - 4 ≤ Stations ≤ 20
        - 0 km ≤ Scenic route ≤ 120 km

3.2 Electric and petrol drivers' comparison hypotheses

A critical consideration in this study is the type of vehicle that the user is driving, in particular the differences between electric cars and petrol cars. With the surge in electric vehicles sales in recent years (Agency, 2024), and their unique concerns associated with range for instance (Franke, 2013), it is essential to investigate how these differences may influence the route adaptation decision of a user. Therefore, the participants were divided into two groups, one who were asked to imagine they are driving a Tesla Model 3 (Electric), the other asked to imagine they were driving a Volkswagen Polo (Petrol). This comparison resulted in the following five hypotheses; the method for testing their statistical significance is detailed in Section 4.6.

6. For the difference in factor stoplights:
    - Null hypothesis (**H0**): There is no difference between drivers of electric cars and petrol cars concerning the influence of the stoplights on route adaptation.
    - Alternative hypothesis (**H1**): There is a difference between drivers of electric cars and petrol cars concerning the influence of the stoplights on route adaptation.
7. For the difference in factor roundabouts:
    - Null hypothesis (**H0**): There is no difference between drivers of electric cars and petrol cars concerning the influence of the roundabouts on route adaptation.

    - Alternative hypothesis (**H1**): There is a difference between drivers of electric cars and petrol cars concerning the influence of the roundabouts on route adaptation.
8. For the difference in factor Highway:
    - Null hypothesis (**H0**): There is no difference between drivers of electric cars and petrol cars concerning the influence of the distance of highway on route adaptation.
    - Alternative hypothesis (**H1**): There is a difference between drivers of electric cars and petrol cars concerning the influence of the distance of highway on route adaptation.
9. For the difference in factor in stations:
    - Null hypothesis (**H0**): There is no difference between drivers of electric cars and petrol cars concerning the influence of the stations on route adaptation.
    - Alternative hypothesis (**H1**): There is a difference between drivers of electric cars and petrol cars concerning the influence of the stations on route adaptation.
10. For the difference in factor scenic views:
    - Null hypothesis (**H0**): There is no difference between drivers of electric cars and petrol cars concerning the influence of the distance of scenic views on route adaptation.
    - Alternative hypothesis (**H1**): There is a difference between drivers of electric cars and petrol cars concerning the influence of the distance of scenic views on route adaptation.

3.3 Conditioned hypotheses

While the research on the impact of a shorter route distance is limited, it is hypothesised that it has a profound impact. This study therefore will examine the impact of the considered factors conditioning on shorter distance. Thus, the subsequent five hypotheses are proposed:

11. The effect of the number of stoplights on the conditioned distance:
    - Null hypothesis (**H0**): The number of stoplights does not influence the user's willingness to adapt the route.
    - Alternative hypothesis (**H1**): The number of stoplights influences the user's willingness to adapt the route.
    - For this hypothesis the following conditions apply:
        1. 20 min ≤ Time ≤ 32 min
        2. 30 km ≤ Distance ≤ 40 km

3. 0 ≤ Stoplights ≤ 8
4. 0 ≤ Roundabouts ≤ 8
5. 0 km ≤ Scenic route ≤ 12 km

12. The effect of the number of roundabouts on the conditioned distance:
    - Null hypothesis (**H0**): The number of roundabouts does not influence the user's willingness to adapt the route.
    - Alternative hypothesis (**H1**): The number of roundabouts influences the user's willingness to adapt the route.
    - For this hypothesis the following conditions apply:
        1. 20 min ≤ Time ≤ 32 min
        2. 30 km ≤ Distance ≤ 40 km
        3. 0 ≤ Stoplights ≤ 8
        4. 0 ≤ Roundabouts ≤ 8
        5. 0 km ≤ Scenic route ≤ 12 km
13. The effect of the distance of highway on the conditioned distance:
    - Null hypothesis (**H0**): The distance of highway does not influence the user's willingness to adapt the route.
    - Alternative hypothesis (**H1**): The distance of highway influences the user's willingness to adapt the route.
    - For this hypothesis the following conditions apply:
        1. 3 hours 30 min ≤ Time ≤ 4 hours
        2. 300 km ≤ Distance ≤ 350 km
        3. 50 km ≤ Highway ≤ 250 km
        4. 4 ≤ Stations ≤ 20
        5. 0 km ≤ Scenic route ≤ 120 km
14. The effect of number of gas / petrol stations on the conditioned distance:
    - Null hypothesis (**H0**): The number of gas / petrol stations does not influence the user's willingness to adapt the route.
    - Alternative hypothesis (**H1**): The number of gas/petrol stations influences the user's willingness to adapt the route.
    - For this hypothesis the following conditions apply:
        1. 3 hours 30 min ≤ Time ≤ 4 hours
        2. 300 km ≤ Distance ≤ 350 km
        3. 50 km ≤ Highway ≤ 250 km
        4. 4 ≤ Stations ≤ 20

        5. 0 km ≤ Scenic route ≤ 120 km

15. The effect of the distance of scenic views on the conditioned distance
    - Null hypothesis (**H0**): The distance of scenic views does not influence the user's willingness to adapt the route.
    - Alternative hypothesis (**H1**): The distance of scenic views influences the user's willingness to adapt the route.
    - For this hypothesis the following conditions apply:
        - 3 hours 30 min ≤ Time ≤ 4 hours
        - 300 km ≤ Distance ≤ 350 km
        - 50 km ≤ Highway ≤ 250 km
        - 4 ≤ Stations ≤ 20
        - 0 km ≤ Scenic route ≤ 120 km

4. Methodology

4.1 Formulated factors

The hypotheses were structured around certain factors and conditions that are divided based on their relevance for a short distance or a long distance. The short distances were defined as routes ranging from 30 km to 50 km, while long distances were between 300 km and 400 km. The time for short routes was set between 20 min and 32 min and for long routes between 3 hours and 30 min and 4 hours. For a short route, the following attributes were included:

- Distance
- Time
- Number of stoplights
- Number of roundabouts
- Distance of the scenic route

Roundabouts and traffic lights were deemed less relevant for long routes as they are typically considered less and encountered relatively little. Therefore, for long routes there were another set of factors that were presented:

- Distance
- Time
- Distance on highway
- Number of gas / charging stations
- Distance of a scenic route

In case of an electric vehicle the number of charging stations was displayed, for a petrol vehicle the number of gas stations was showed instead. The distance of highway travelled and the number of gas / charging stations were considered to be less applicable on short distance, as they are not used as much on a short range.

Each time a set of 3 questions focussed on one of the factors derived from the hypotheses, an example of such a question is later presented in Figure 1. This was done by randomizing the factor to be different and unique in each option, while keeping all the other factors consistent across the presented options. To evaluate the importance of each factor time was added as a variable factor, being unique for each option. With time as a variable, an analysis can be done on how much driving time users are willing to extend for each distinct factor. This method enables a deeper examination of the relative weight of each attribute in relation to time.

4.2 Identifying subgroups

Finally, information about the participants was asked to identify if certain subgroups act differently. This includes:

- Age
- Gender
- Country of residence
- Educational level
- Employment status
- Household annual income
- Size of the household
- Possession of driver license

If the participant had a driver license further information could be relevant to identify more subgroups:

- Duration of driving experience
- Frequency of driving
- Type of propulsion for the vehicle they usually drive
- Vehicle ownership status
- Choice of navigation apps
- Frequency of navigation app usage
- Preferred travel method to work/school

4.3 Survey distribution and design

The data was obtained in two ways:

1. Distribution of the link of the survey in the author's network by WhatsApp and Instagram, including contacts of my parents to diversify the population more.
2. Making use of an online service called Prolific that specializes in the distribution of surveys.

The participants were not filled in on the precise goal of the research to prevent biases. They also only saw the electric or petrol version of the survey.

The design of the survey was done in Qualtrics and had the following sequence:

1. The participant started with an introduction which thanked them for their participation and gave contact information for possible questions.

2. Then the questions about their information such as age and gender were presented.

3. It was ensured in the flow of the survey, with help of an "IF" branch, that the person only got asked about their driving behaviour next if they answered "YES" to the question about their possession of a driver license. The questions about the choice of navigation app were not mandatory as not everybody uses these.

4. Before starting the questions about the factors an introduction was shown with the following text to explain what a participant needed to know:
   "For the next questions imagine you are driving [electric or petrol vehicle] to your work. Please choose the route that you would like to use based on the travel distance and travel time, the number of roundabouts and stoplights, the distance on highway, as well as the distance with scenic views. Note that a scenic route is a path that offers beautiful views and enjoyable driving experiences. It might pass through forests, along water, or by nice buildings, providing a more visually pleasant journey."

5. Next followed a block of 3 questions with each 3 options that tested one particular factor. For question 1 for example there were three provided options as shown in Figure 1.

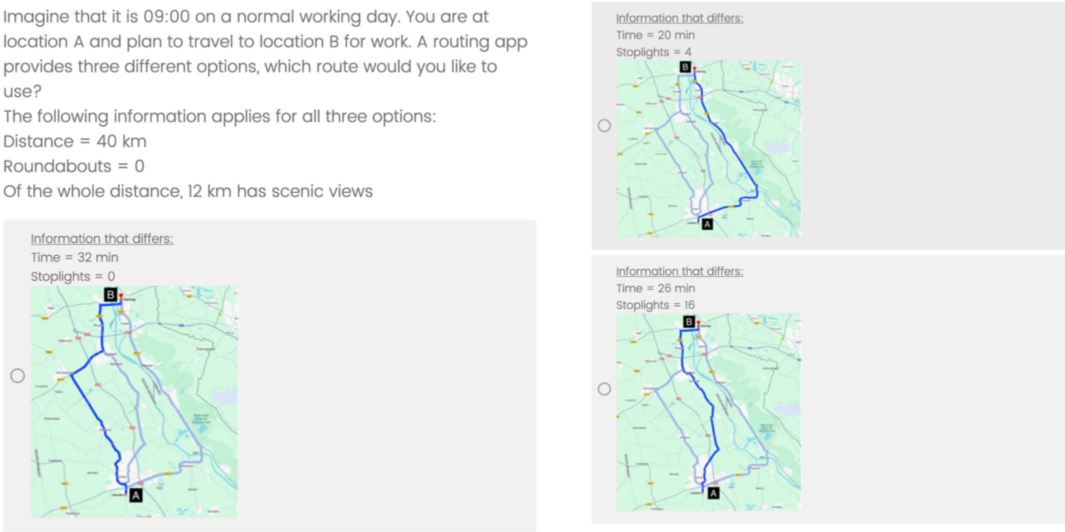

Figure 1. An example of a question that is presented to the responded

The question started with reminding the participant to imagine they were in a certain situation. This situation is the same for every question to ensure that it had no influence on the results of the survey. Then the person was provided with the information, which was the same for each route to guarantee clarity. For each options the time and another factor were shown with a visual representation of the navigation in Google Maps. The routes were different locations throughout Europe, with each three different options that minimally intertwined to get from one destination to another. To prevent unclarity an A and B point were added to the images.

6. This process was repeated until all 15 questions were completed.

7. At the end of the survey the "Workers" from the online survey received a personalised code. The provided code could be used on the website to confirm that they had indeed completed the survey.

To randomise the values every time 5 different possible values were chosen for each factor. These were:

- Distance (short) = [30 km, 35 km, 40 km, 45 km, 50 km]
- Distance (long) = [300 km, 325 km, 350 km, 375 km, 400 km]
- Time (short) = [20 min, 23 min, 26 min, 29 min, 32 min]
- Time (long) = [3 hours and 30 min, 3 hours and 37 min, 3 hours and 45 min, 3 hours and 52 min, 4 hours]
- Stoplights = [0, 4, 8, 12, 16]

- Roundabouts = [0, 4, 8, 12, 16]
- Highway = [50 km, 100 km, 150 km, 200 km, 250 km]
- Stations = [4, 8, 12, 16, 20]
- Scenic route (short) = [0 km, 3 km, 6 km, 9 km, 12 km]
- Scenic route (long) = [0 km, 30 km, 60 km, 90 km, 120 km]

Within Qualtrics, JavaScript was used to randomise each factor. First there was an array defined for each factor and their possible values. Next a function was created to shuffle set arrays. This function was consequently used to shuffle the arrays for each participant. For each question the embedded data was given a value from the array and each option got assigned a different index to ensure the options were unique.

4.4 The Bradley-Terry model

To analyse the results, the Bradley-Terry model was utilised to determine the impact of each of the considered factors: the Bradley-Terry Model (Guo, 2018) is a method in which pairs are compared to predict the likeness of one being chooses over the other. The model is based on probabilistic assumptions and utilizes both absolute and comparison labels.

First there exists parameter vector $\beta \in \mathbb{R}^d$ exists which is sampled from a Gaussian prior $N(0, \sigma^2 I)$, so that for all $i \in N$ and all $(i, j) \in C$. N represents the set of all items considered and C represents the set of all possible pairs from N that are being compared. The absolute labels Y_i and comparison labels $Y_{i,j}$ are independently conditioned on β. Secondly the conditional distribution of Y_i given x_i and β is provided by a logistic model:

$$P(Y_i = +1 | x_i \beta) = \frac{1}{1 + \exp(-\beta^T, x_i)}, \qquad i \in N.$$

Finally the conditional distribution of $Y_{i,j}$ given x_i x_j and β is given by the Bradley-Terry model, here it is assumed that every item of $i \in N$ is associated with a parameter $s_i \in \mathbb{R}^+$s.t. $P(Y_{i,j} = +1) = \frac{s_i}{(s_i + s_j)}$ for all $(i, j) \in C$. This brings us to the following equation incorporating $x_i \in \mathbb{R}^d$, $i \in N$:

$$P(Y_{i,j} = +1 \middle| x_i, x_j, \beta) = \frac{s(x_i, \beta)}{s(x_i, \beta) + s(x_j, \beta)}, \qquad (i, j) \in C.$$

where $s(x_i, \beta) = e^{\beta^T x_i}$.

Although the discussion focuses on a single expert, the probabilistic nature of this model allows for incorporating multiple experts generating independent labels over the same pairs.

In the case of this research, the participants each have three options instead of two. To generate the preference data set, if the expert prefers option O_i over O_j, and O_k, then we add two pairs $O_i > O_j, O_i > O_k$ to the dataset.

The process started in Python by reading the csv file and cleaning it. The cleaned data was used to pair each response to a question with the right values of each differentiating factor, one of them being always time. This resulted in two pairs for each question, as there were three options. Using Pandas, a DataFrame was generated containing al these pairs that could be used to fit the Bradley Terry model on the data. The items in this research were the different routes that were presented, and they were compared each time on one factor and the travel time. This meant that each factor, including the travel time, had an associated parameter showing its effect on the preference of the user. The following model is formulated; given two items i and j with the associated parameters θ_i and θ_j:

$$P(i\ is\ preferred\ over\ j) = \frac{\theta_i}{\theta_i + \theta_j}$$

In the survey each route can be described these factors and travel times:

- T_i (Travel time for route i)
- $x_{i,Stoplights}$
- $x_{i,Roundabouts}$
- $x_{i,Highway}$
- $x_{i,Stations}$
- $x_{i,ScenicRoute}$

The parameters than can be described as a function of these factors:

$$\theta_i = \exp(\beta_{Time} \cdot T_i + \beta_{Stoplights} \cdot x_{i,Stoplights} + \beta_{Roundabouts} \cdot x_{i,Roundabouts} + \beta_{Highway} \cdot x_{i,Highway} + \beta_{Stations} \cdot x_{i,Stations} + \beta_{ScenicRoute} \cdot x_{i,ScenicRoute})$$

Where β are the parameters to be estimated.

Using this model, the parameters β describe the effect of each factor, where $\beta < 0$ indicates that an increase in the factor leads to a decrease in user preference for the route.

The trade-off with time for a given factor i could be determined by how much time β_{Time} the participant was willing to add or reduce a given factor, by calculating it as follows:

$$T = \frac{\beta_i}{\beta_{Time}}$$

4.5 Bootstrapping and standardisation

To further analyse the data, we used bootstrap resampling to identify the confidence interval (CI). First the Bradley-Terry model was fitted to the original data set to estimate the initial parameters. Then several bootstrap samples were generated, in this case 20, by randomly sampling with replacements from the original dataset. For each bootstrap sample a Bradley-Terry model was fitted, and the results were recorded. Each parameter had its own empirical distribution based on the estimates from the bootstrap samples. Moreover, confidence intervals were calculated from the empirical distributions. This was done by the sorting the bootstrap estimates in ascending orders. For the 95% CI that was used in this study, the 2,5th percentile and the 97,5th percentile were determined. In this study, a factor is defined as statistically significant if its CI did not include zero; if zero was in the range of the interval, the factor was considered not significant.

However, to determine the relative importance of each factor a standardisation was needed before fitting the model. The Z-score considered for this purpose was:

$$Z_i = \frac{X_i - \mu}{\sigma},$$

where μ is the mean and σ the standard deviation of the dataset.
This was used in all further analyses of subgroups to determine the importance of each factor.

4.6 Confidence intervals in comparisons

To identify if the differences between certain subgroups was significant, the CI was used. However, directly comparing the 95% CIs commonly leads to mistakes when concluding significance by determining if there is no overlap between the two intervals. This is why Goldstein and Healy proposed a different method (Goldstein, 1995). Instead of directly comparing the CIs, the CI of the means is compared. For two independently distributed means m_i with m_j with known standard errors σ_i and σ_j, the condition can be determined under which they do not overlap, under the assumption of normality. This can be described as follows:

$$|m_i - m_j| > z_p(\sigma_i + \sigma_j),$$

where z_p is the z-score corresponding to the confidence level α. For this analysis with a 95% CI, where $z_{0.025} = 1.96$.
To evaluate the probability that this inequality holds, the ratio of standard errors $\frac{\sigma_i}{\sigma_j}$ is considered. Using the normal distribution's cumulative distribution function $\Phi(z)$, the probability P that the confidence intervals do not overlap can be expressed as:

$$P = 2\left(1 - \Phi\left(z_p \frac{\sigma_i + \sigma_j}{\sqrt{\sigma_i{}^2 + \sigma_j{}^2}}\right)\right),$$

This probability varies depending on the ratio $\frac{\sigma_i}{\sigma_j}$ and is minimized when the ratio is equal to 1.

When $P < 0.05$, it indicates that the CIs do not overlap, suggesting a significant difference between the means. Conversely, if $P \geq 0.05$ it indicates the CIs do overlap, meaning the difference is not statistically significant. This study chooses to use visual approach to determine if the CIs overlap, this allows for a more intuitive and clearer comparison between the various subgroups. If the CIs of the means do not include the zero line on the graph, the difference between the means is found to be statistically significant.

5 Results

5.1 Population distribution

The population of the respondents is as displayed in Table 1 and 2.

	Number of respondents
Total	100
Age	
19-24	50
25-34	28
35-44	13
45-59	8
60 ≥	1
Gender	
Male	65
Female	33
Non-binary	2
Country of household	
Armenia	1
Belgium	3
France	4
Germany	1
Greece	3
Ireland	5
India	1
Lithuania	3
Netherlands	53
Philippines	9
Portugal	9
Sudan	5
Italy	2
Education level	
Less than high school	0

High school	17
Some college	15
2-year degree	11
4-year degree	23
Professional degree	30
Doctorate or higher	4
Personal situation	
Employed full time	39
Employed part time	15
Unemployed	6
Retired	1
Student	39
Household annual income	
Less than €10.000	33
€10.000 - €29.999	24
€30.000 - €49.999	16
€50.000 - €69.999	11
€70.000 - €89.999	3
€90.000 - €149.999	10
More than €150.000	3
Household size including the responded	
1	35
2	14
3+	51
Possession of driver license	
Yes	93
No	7

Table 1. The population of total survey

	Number of respondents with a driver license
Total	93
Driving experience	
Less than 1 year	1
1-2 years	11
3-5 years	31
6-10 years	23
More than 10 years	27
Driving frequency	
Daily	31
A few times a week	25
Once a week	3
A few times a month	16
Rarely	17
Never	1
Propulsion type of the usually driven vehicle	
Petrol	47
Diesel	23
Hybrid	7

Electric	16
Vehicle ownership	
Own	50
Lease	4
I do not have a vehicle	39
Navigation app choice	
Google Maps	55
Waze	4
Other	5
Navigation app usage	
Daily	13
A few times a week	34
Once a week	12
A few times a month	24
Rarely	8
Never	2
Preferred travel method	
Walking	9
Cycle	27
Motorcycle	1
Car	31
Public transport	25

Table 2. The driving behaviour of participants with a driver license

The data was gathered in two distinct ways, one through the author's network and one through an online website distributor. Both methods gathered exactly 50 finished responses. The Bradley-Terry model was performed with the bootstrap method to generate the CIs of both groups. The CIs of the means is utilised to investigate if the data was consistent. In Figure 2 the results are presented from the table in appendix A.

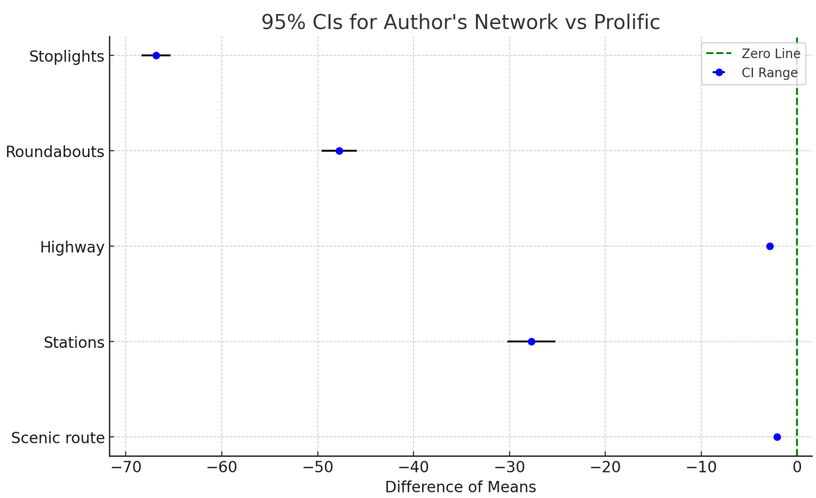

Figure 2. The CIs of the means for the two distribution channels

In Figure 2 the interval plot is displayed, with the green zero line representing no difference between the groups. Here it can be observed that there are significant differences for all factors. All the differences of means are negative indicating that the author's network was relatively more sensitive than the group from the website Prolific. This should be considered further in the study.

5.2 Data processing

The survey for electric vehicles got 49 responses and the survey for petrol vehicles got 51. The results of the survey were exported to a .CSV file so it could be used in Python as a data frame. Before fitting the model, the results were standardized. The Bradley-Terry model was used, as described in Section 4.4, to calculate the parameters for each factor using this formula:

$$P(i \text{ } is \text{ } preferred \text{ } over \text{ } j) = \frac{\theta_i}{\theta_i + \theta_j},$$

where θ_i is the parameter option i.

Using these parameters the trade-off with time can be calculated with the following formula, as described in Section 4.4:

$$T = \frac{\beta_i}{\beta_{Time}}$$

The standardized coefficient in Table 3 represents the θ value of each factor, influencing the likelihood of preference. A higher absolute value indicates a stronger impact on the route preference. The bootstrap method is utilised to calculate the 95% CIs for each factor.

Factor	**Standardized coefficient**	**Standardized bootstrap CI**		**Trade-off with time**
		Lower bound	**Higher bound**	
Stoplights	-0.133	-0.148	-0.116	1.106
Roundabouts	-0.093	-0.105	-0.078	0.775
Highway	0.004	0.002	0.005	-0.029
Stations	0.018	0.007	0.038	-0.153
Scenic route	0.015	0.013	0.017	-0.125
Time	-0.120	-0.128	-0.114	*

Table 3. The output of the Bradley-Terry model and bootstrap method for the data

The interpretation of the trade-off time differs based on them having a positive or negative value. For instance, the 1.106 trade-off time for stoplights means that a responded was willing to add 1.106 stoplights to their route for every additional minute driven less. This is because the negative parameter for both stoplights and time is indicating that participants are estimated to prefer less of them. For the factor stations on the contrary the responded was willing to reduce the number of stations by 0.153 for every minute saved on their trip.

5.3 Testing the hypotheses

For all other results the values were standardised before fitting the Bradley-Terry model to be able to compare them. For the entire data set the following results were generated. The bootstrap CI values enabled the tests for the first five hypotheses as shown in Table 4, with the help of the standardized coefficient Figure 3 was created to visualise the influence of the various factors.

Hypothesis	Factor	Standardized coefficient	Trade-off with time	Standardized Bootstrap CI	Reject H0
1	Stoplights	-8.965	74.838	[-9.821, -8.301]	Yes
2	Roundabouts	-6.282	52.440	[-7.191, -5.780]	Yes
3	Highway	0.237	-1.977	[0.152, 0.329]	Yes
4	Stations	1.243	-10.380	[0.197, 2.605]	Yes
5	Scenic route	1.010	-8.429	[0.805, 1.139]	Yes
*	Time	-0.120	*	[-0.127, -0.111]	*

Table 4. The standardized output of the Bradley-Terry model and bootstrap method for all data

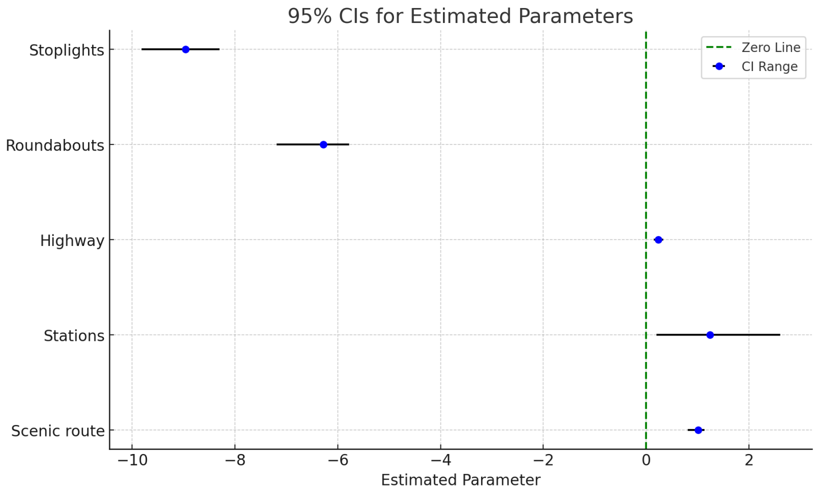

Figure 3. The CI's and the estimated parameters of the original data

In Figure 3 the various CIs for each factor is displayed, with a blue point representing the estimated parameters from the initial data set. The green vertical line represents an influence of zero, if crossed by the interval the **H0** of the hypothesis is not rejected as the result is not significant. In this case it is clear from the results that all five factors have an impact on the decision of the participant to choose a route over another and all **H0** are rejected. Stoplights and roundabouts have a negative impact and the largest impact respectively. The other three factors are of positive influence, influencing considerably less however than the negative factors.

The next five hypotheses focussed on the differences between electrical drivers and petrol drivers. Both the data sets showed the following results.

Factor Electric	Mean standardized coefficient	Standardized bootstrap CI		Trade-off with time
		Lower bound	Higher bound	
Stoplights	-9.883	-11.100	-8.407	74.423
Roundabouts	-7.329	-8.350	-6.643	55.191
Highway	0.399	0.267	0.557	-3.008
Stations	2.083	0.056	4.015	-15.684
Scenic route	1.328	1.103	1.505	-10.003
Time	-0.133	-0.145	-0.124	*

Table 5. The standardized output of the Bradley-Terry model and bootstrap method for the data

Factor Petrol	Mean standardized coefficient	Standardized bootstrap CI		Trade-off with time
		Lower bound	Higher bound	
Stoplights	-8.487	-9.490	-7.285	75.992
Roundabouts	-5.443	-6.423	-3.726	48.735
Highway	0.089	-0.080	0.212	-0.799
Stations	0.308	-1.308	1.867	-2.757
Scenic route	0.771	0.541	0.995	-6.906
Time	-0.112	-0.122	-0.103	*

Table 6. The standardized output of the Bradley-Terry model and bootstrap method for the data

From the results from Table 5 and 6 the standardized bootstrap estimated parameters and the trade-off with time were used to determine the confidence intervals of the difference as shown in Table 7. From the CIs and the difference of the trade-off a confidence interval plot is created that is presented in Figure 4.

Hypothesis	Factor	Difference in trade-off	CI of difference	Reject H0
6	Stoplights	-1.569	[-3.309, 0.172]	No
7	Roundabouts	6.457	[4.861, 8.052]	Yes
8	Highway	-2.209	[-2.415, -2.003]	Yes
9	Stations	-12.927	[-15.464, -10.390]	Yes
10	Scenic Route	-3.097	[-3.400, -2.794]	Yes

Table 7. The confidence intervals of the difference between electrical and petrol

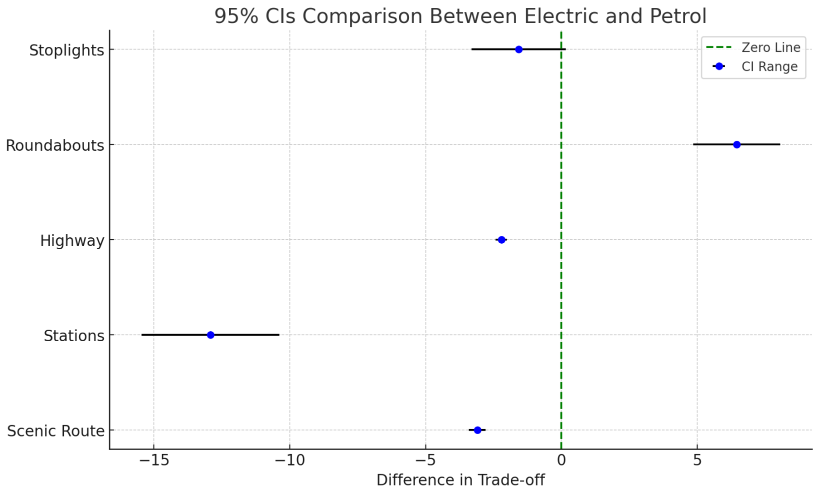

Figure 4. The CIs difference of means for electric compared to petrol

It is evidently shown in Figure 4 that the CI of stoplights crosses the green line, indicating it is in the range of 0 and thus not significant. All other factors have their **H0** rejected establishing that with these factors there is a difference between electrical and petrol drivers. Note that the definition of the green line is distinct in the interval plot for a comparison, as it is centred around the green line. The negative part of the x-axis represents a greater influence the electric drivers, while the positive axis represents a greater influence on petrol drivers. The factor station shows the largest difference, influencing electric drivers the most. Roundabouts meanwhile is the second largest, only this factor has a bigger impact on petrol drivers.

The last 5 hypotheses were based on conditioned distances, for this only the responses were used that were shorter and thus for which applied that 0 km ≤ Scenic route ≤ 12 km or 0 km ≤ Scenic route ≤ 120 km. The results of the tests on hypotheses 11 to 15 is displayed in Table 8 and Figure 5.

Hypothesis	**Factor**	**Standardized Coefficient**	**Trade-off with time**	**Standardized Bootstrap CI**	**Reject H0**
11	Stoplights	-8.685	68.570	[-9.682, -7.274]	Yes
12	Roundabouts	-5.818	45.936	[-6.990, -4.600]	Yes
13	Highway	0.324	-2.560	[0.236, 0.508]	Yes
14	Stations	1.222	-9.645	[-0.374, 2.544]	No
15	Scenic route	1.154	-9.114	[0.908, 1.395]	Yes
*	Time	-0.127	*	[-0.136, -0.118]	*

Table 8. The output of the Bradley-Terry model and bootstrap method for the conditioned data

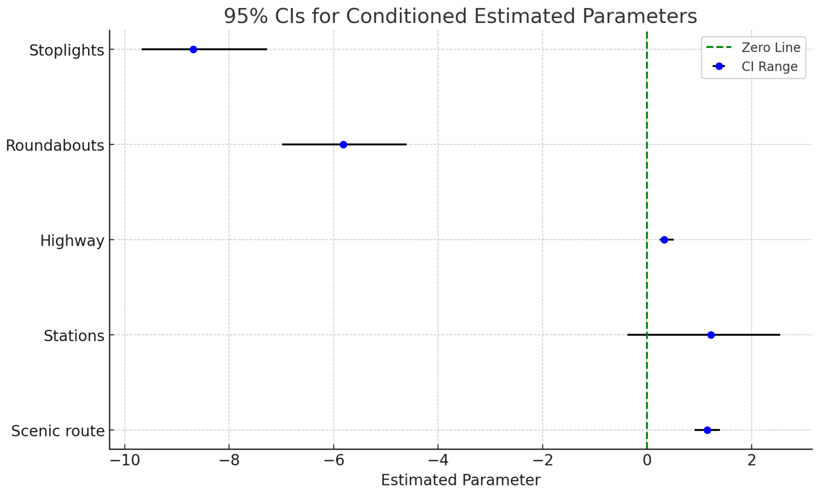

Figure 5. The CI's and the standardized coefficients of the conditioned data

Similar as in the original data set, the stoplights and roundabouts have the most impact on the respondent's choice for a navigation suggestion. Unlike the original data the factor stations is not significant here. Highway has the smallest value accompanied by the smallest range as it was in the original data.

5.4 Subgroups comparisons

For this section the various subgroups were analysed based on the population distribution to identify any discrepancies in preferences between them. This is done using the CI differences for each factor at a time to present the results more clearly. The subgroups country of residence, possession of driver licence, navigation app choice, and preferred travel method were not included as the sizes of the groups are insufficient for a proper analysis. The subgroup comparisons are presented for each factor to give a clear overview. These should be interpreted as follows; a negative value means the first subgroup is more influenced by the factor, a positive value translates into the second group being more influenced by the factor. In Table 9 the subgroups are provided, being constant in every analysis. Figures 6-9 are based on the results from the comparison of the confidence interval of the means, which can be found in appendix B-F.

Attribute	**Subgroups**	
	1	**2**
Age	24 ≤	25 ≥
Gender	Male	Female
Educational level	2-year degree ≤	4-year degree ≥
Personal situation	Student	Other
Annual income	€20.000 <	€20.000 ≥
Household size	1 and 2	3 ≥

Driving experience	5 years ≤	6 years ≥
Driving frequency	A few times a week ≤	Once a week ≥
Vehicle type driven usually	Petrol	Other
Vehicle ownership	Own or lease	No
Navigation app usage	A few times a week ≤	Once a week ≥

Table 9. The subgroups used for the analyses

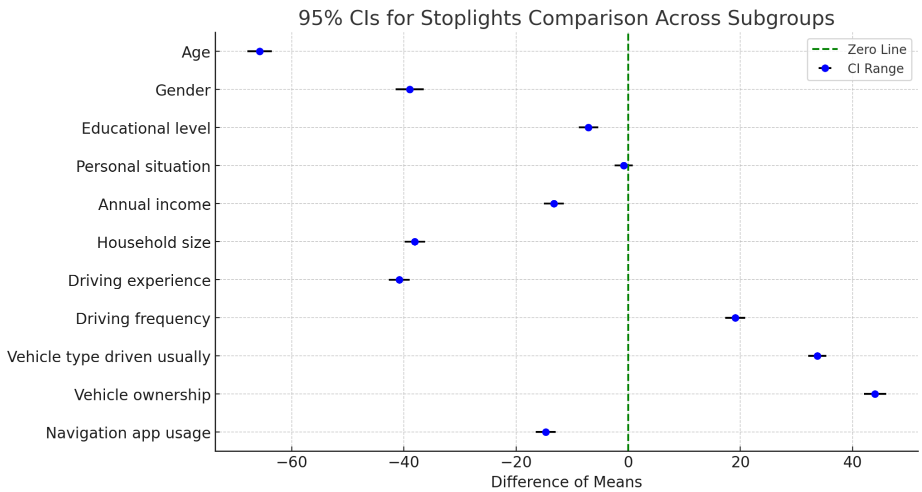

Figure 6. The CIs difference of means for each subgroup for stoplights

In Figure 6, the distinct difference in the influence of stoplights is seen in the subgroup age. With persons of an age of 24 or lower being more prone for stoplights with a difference in trade-off of -65.729. All other subgroups show significant discrepancies too, besides the personal situation that did not have any significant differences as its CI range crosses the zero line.

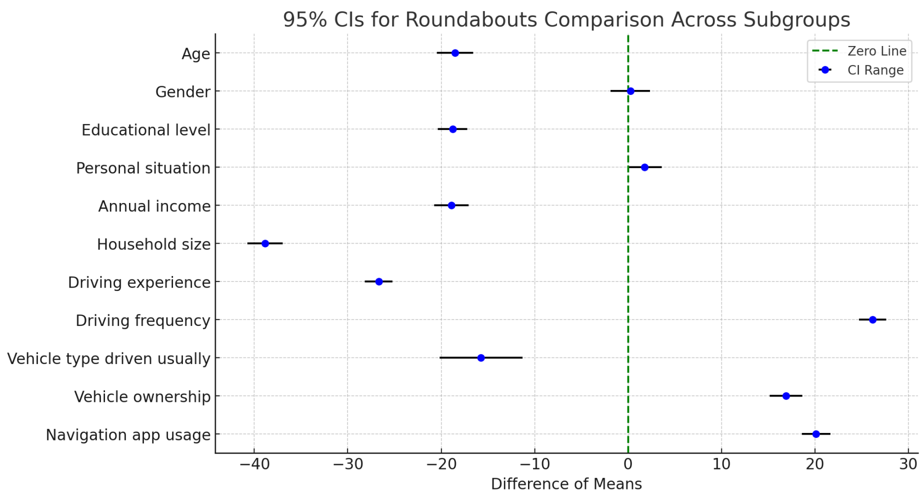

Figure 7. The CIs difference of means for each subgroup for roundabouts

First of the gender and personal situation do not merit a significant difference on the behaviour of participants. The household size has the largest mean with -38.861. The subgroup that drives a petrol car is more impacted by roundabouts than other drivers, which is in line with the previous findings for hypothesis 7. It also worth mentioning that drivers who drive more frequently are keener on avoiding roundabout, like they also were in Figure 6 for stoplights. The opposite is true for driving experience.

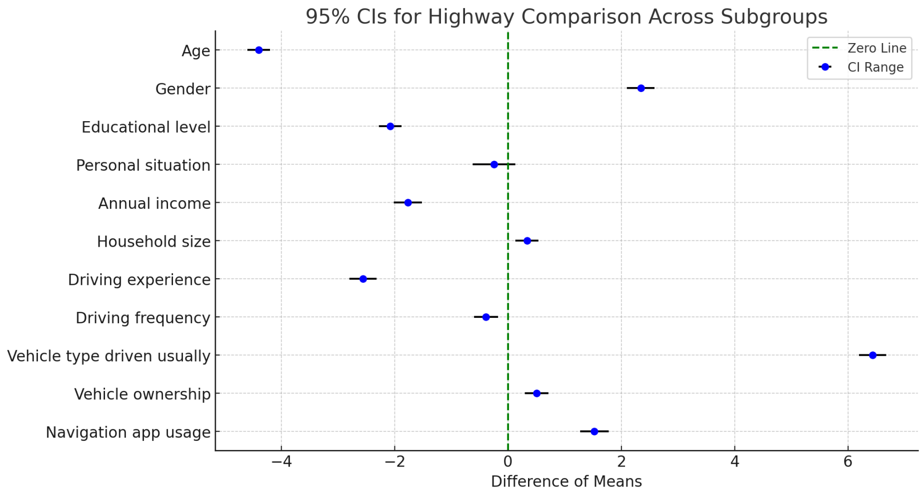

Figure 8. The CIs difference of means for each subgroup for highway

For the distance of highway, it is notable that petrol drivers are much less sensitive to this factor than other drivers. The similar situation is true for persons with the age of 25 years or older.

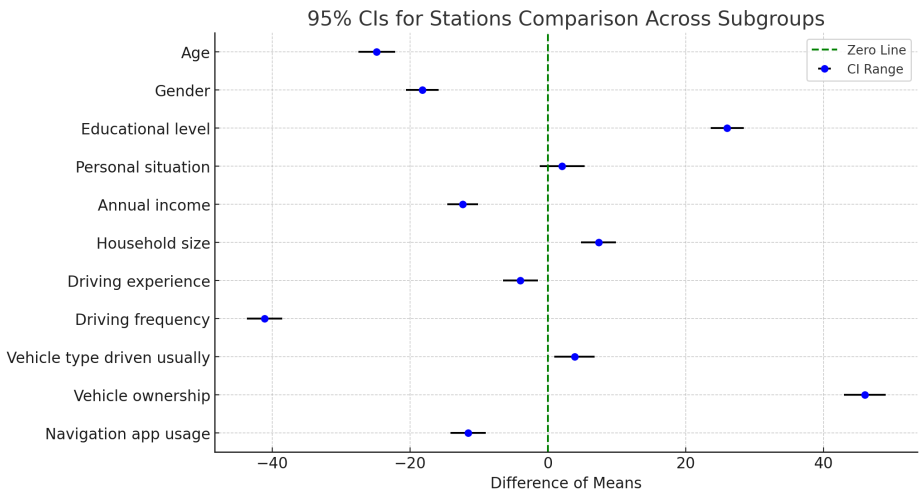

Figure 9. The CIs difference of means for each subgroup for stations

One of the critical findings in Figure 9 is that vehicle ownership has the most substantial difference between owners and no owners. It also shows that the number of stations has a sizeable influence on drivers with an experience 5 years or less and the group of 24 years old or younger. For the educational level applies that the higher educated persons were wearier of the number of stations along their road. The differences are relatively high in Figure 9 as can be seen on the x-axis.

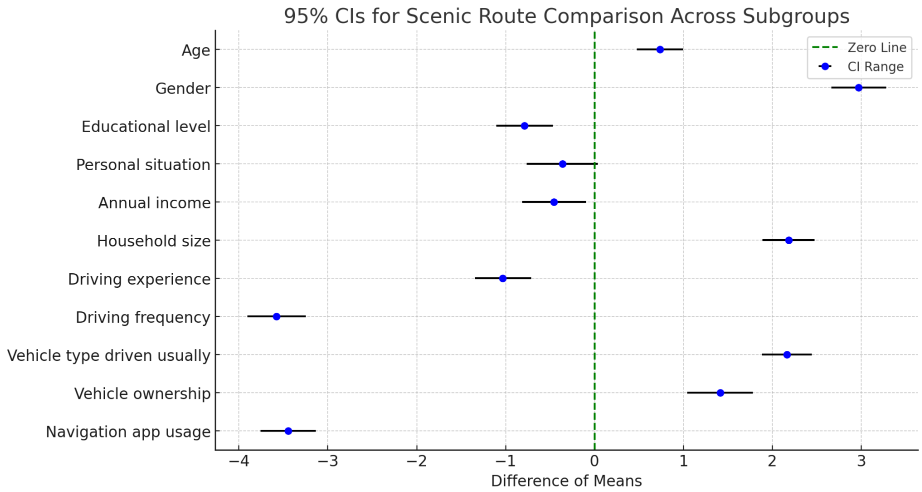

Figure 10. The CIs difference of means for each subgroup for scenic route

Figure 10 shows that the subgroups of minimal navigation app usage and not frequent drivers are more influenced by the distance of scenic route. Women are more susceptible for scenic routes than men according to data. In general, the personal situation has not have had a significant influence on any of the factors.

6 Discussion & conclusion

6.1 Implications

The results of this study have some implications on the understanding of how users interact with AI-generated navigation suggestions. In Table 4 it is demonstrated that the bootstrap CIs rejected the **H0** for hypotheses 1 to 5, thereby supporting the alternative hypotheses of **H1**. These findings indicate that the factors examined - number of stoplights, roundabouts, distance on highways, number of stations, and scenic views - do indeed influence the choice of the user to adapt a route from their AI navigation system.

The analysis revealed that the factors stoplights and roundabouts were experienced as undesirable and had more substantial impact with a trade-off time of 74.838 and 52.440 respectively. This outcome likely reflects the human tendency to dislike traffic and minimize stopping their car. The stronger aversion for stoplights compared to roundabouts can be attributed to the fact that drivers typically stopping fewer times at a roundabout, aligning with the previously mentioned desire to continuously move.

On the contrary, the other factors were found desirable, tough they had less of an impact on the decision-making process. Notably, participants were less inclined to drive longer if it meant an increase in one of these factors. In particular the distance of highway, which had the most minimal influence with a trade-off of -1.977 and the smallest CI [0.152, 0.329]. This may be explained by the concept of negative bias, the human tendency to focus more on the negative stimuli than the positive ones (Vaish, 2008).

The 6th hypothesis was found to be not significant and thus we cannot deduce that the stoplights influence is different between a person driving either an electrical vehicle or a petrol one, as depicted in Figure 4. The other four hypotheses concerning this comparison were found to be significant, as illustrated in Table 7. Among these, the number of stations displayed the most considerable difference of -12.927, indicating electrical drivers are influenced more. This is consistent with the expectation that drivers of an electric vehicle would have a greater concern for the range of their battery.

In Table 8 it is shown that the hypotheses 11 to 15 that were conditioned for shorter distances rejected all **H0** hypotheses, except for the number of stations. The diminished importance of stations on a shorter distance is logical, as the need for recharging and refuel is reduced. In Figure 5 the stoplights and roundabouts were found to have the most significant impact, while the impact of distance of highway was minimal again, similar to the analysis of the original data. The decrease in trade-off scores in general could be accounted for by perceived smaller differences on shorter distances.

Several noteworthy results emerged from the subgroup analyses. Firstly, individuals who drove frequently exhibited a stronger inclination to evade stoplights and roundabouts, as demonstrated by Figures 6 and 7. This behaviour may be caused by the increased frustration with these types of crossings associated with encountering them regularly. Figures 6 and 7 interestingly display that driving experience has the opposite effect, indicating that individuals who have had their driver license for 5 years or less were more influenced by these factors. These findings align with similar results of the subgroup age, as evidenced Figures 6 and 7, as younger individuals have their driver license shorter. The reason for the significant difference observed in Figure 6 for the subgroup without vehicle ownership remains unclear.

In Figure 9 highlights age, the educational level, and the driving frequency as the three subgroups with the most substantial differences. The subgroup with the higher educational level was influenced substantially more by the factor stations, with a trade-off time difference of

26.000. The younger group and the less frequent drivers may choose for the safer options due to their limited experience in uncertain situations. In Figure 9 it also shown that petrol car owners were only marginally less concerned with stations, in contrast with the comparison for electrical and petrol vehicles. This discrepancy could be attributed to the other group including hybrids and diesel, beside electrical vehicles.

This group of other vehicle owners exhibited the largest difference in Figure 8, with a mean of 6.433. The variations of means are small in this Figure 8, likely because highway did not have a wide CI in the original data set, giving little space for differences. The factor scenic route does not display any substantial differences between the various subgroups, as it should be noted that Figure 10 has the lowest values on its x-axis, despite not having the lowest trade-off time in the original data.

Finally, in Figures 5-9 it is observed that individuals who do not own a vehicle were more influenced by all the factors. This increased sensitivity may be due their inexperience with all these factors, prompting them to pay closer attention to these elements, rather solely focussing on the travel time.

The Driver Preference-Based Route Planning model, developed by Wang et al. (2022), incorporate the attributes scenery and traffic lights into the route selection process. As displayed by the outcomes of hypotheses 1 and 5, this study supports that decision, finding both attributes to be of significant importance to users' preferences. The scenic quality was also found to be of impact in the study of Amirgholy et al. (2017), further validating its relevance. Additionally, the difference of electrical and petrol drivers in this research agrees with the study of Franke, T., & Krems, J. F. (2013) that suggests that electrical drivers are weary of their battery range and charging opportunities. It is remarkable, however, that younger drivers look to be more careful from this data as study finds that younger persons are more likely to take risks in everyday activities (Ivers, 2009).

Furthermore, this research contributes to the existing body of knowledge by identifying and confirming factors that have a significant influence on driver's preferences when selecting a route. These factors could be leveraged to further refine AI navigation systems. Especially by integrating considerations for electrical vehicles, with the availability of charging stations along the road being crucial. The data also demonstrated that in specific context, like the conditioned shorter distance, factors like stations could be of no significant influence. This indicates that the process of designing and enhancing AI routing systems a broader range of factors should be considered.

The observed variations within subgroups also underscore the necessity for personalisation in AI navigation systems. The system could gather or request background information and preferences to further enhance the experience. This level of personalisation will only become more feasible with continued advancements of AI technologies in the future. For instance, the significant influence of age on preferences, as demonstrated in this study, could be utilised as an attribute for recommendations.

6.2 Conclusion

While numerous studies have focussed on the improvement of AI navigation suggestions from the technical perspective, this research aimed to approach this challenge from the angle of the end-user. Five key factors of interest were identified, corresponding hypotheses were formulated and tested trough a survey. The results of the study provide an answer to the research question:

How can AI-generated routes be improved to better adapt to user needs?

In conclusion the following factors were found to have a significant influence on the Adaptation of AI-generated routes:

- Number of traffic lights
- Number of roundabouts
- Distance on highway
- Number of gas / charging stations
- The distance of a scenic route

This implies that all these factors should be carefully considered when designing an AI routing system. In particular the number of stations is important to consider when focussing on electrical vehicles. Moreover, the observed differences between the various user groups underlines the need for incorporating personalised route suggestions to improve user adaptation further. This is a valuable goal as an increase in adaptations leads to mitigating congestion and less traffic accidents (Metz, 2023; van Rooijen, 2008). Moreover, the wider adaptation of more efficient AI routes also leads to a reduction of carbon emissions (Ranyal, 2022).

6.3 Limitations and future research

One of the limitations was the static environment of the scenario in this study. The respondents were only asked to imagine they were in a single specific situation to prevent other factors from interfering, driving at 09:00 for the purpose of work. Future study could explore a variety of scenarios, studying attributes as time of day and purpose of travel as factor. This would potentially reveal variations in driver behaviour and preferences.

Another limitation the specific focus on cars by this study. This study did not account for drivers of other vehicles, like trucks or motorcycles, who may have different desires. The analysis also showed a difference between the responses of the author's network and the distribution by website. Future research could look at cultural differences between end-users and how these effect their preferences.

A further limitation of this study was the hypothetical nature of the survey. Although the survey did ask participants to imagine they were in a certain situation, it does not replicate the exact same real-life scenario. Observing and tracking actual user behaviour on car navigation systems would likely merit more applicable results. There remains a broad scope of factors and situations to be studied further, to understand the end-user of these systems better.

6.4 Acknowledgements

I wish to express my gratitude to my supervisor Dr. Yingjie Fan for assisting me in shaping this thesis. In this process her flexibility, feedback, and insights have helped me a great deal to advance and eventually complete my research.

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Appendix

Factor	Difference in trade-off	Difference in trade-off	
		Lower bound	Higher bound
Stoplights	-66,857	-68,389	-65,326
Roundabouts	-47,757	-49,583	-45,931
Highway	-2,848	-3,038	-2,658
Stations	-27,723	-30,219	-25,227
Scenic route	-2,110	-2,433	-1,787

Appendix A. The CI of difference and the difference in trade-off for distribution channels

Subgroup	Subgroups		Difference in trade-off	CI of difference	Significant
	1	2			
Age	24 ≤	25 ≥	-65.729	[-67.910, -63.547]	Yes
Gender	Male	Female	-38.929	[-41.424, -36.433]	Yes
Educational level	2-year degree ≤	4-year degree ≥	-7.079	[-8.788, -5.371]	Yes
Personal situation	Student	Other	-0.796	[-2.433, 0.842]	No
Annual income	€20.000 <	€20.000 ≥	-13.249	[-15.026, -11.472]	Yes
Household size	1 and 2	3 ≥	-38.054	[-39.871, -36.236]	Yes
Driving experience	5 years ≤	6 years ≥	-40.801	[-42.678, -38.923]	Yes
Driving frequency	A few times a week ≤	Once a week ≥	19.060	[17.284, 20.837]	Yes
Vehicle type driven usually	Petrol	Other	33.697	[32.068, 35.326]	Yes
Vehicle ownership	Own or lease	No	43.979	[41.993, 45.965]	Yes
Navigation app usage	A few times a week ≤	Once a week ≥	-14.692	[-16.492, -12.892]	Yes

Appendix B. The CIs of the difference between each subgroup for stoplights

Subgroup	Subgroups		Difference in trade-off	CI of difference	Significant
	1	2			
Age	24 ≤	25 ≥	-18.523	[-20.447, -16.599]	Yes
Gender	Male	Female	0.245	[-1.881, 2.371]	No
Educational level	2-year degree ≤	4-year degree ≥	-18.772	[-20.343, -17.201]	Yes
Personal situation	Student	Other	1.770	[-0.050, 3.590]	No
Annual income	€20.000 <	€20.000 ≥	-18.927	[-20.772, -17.082]	Yes
Household size	1 and 2	3 ≥	-38.861	[-40.764, -36.959]	Yes
Driving experience	5 years ≤	6 years ≥	-26.684	[-28.168, -25.199]	Yes
Driving frequency	A few times a week ≤	Once a week ≥	26.179	[24.739, 27.620]	Yes
Vehicle type driven usually	Petrol	Other	-15.754	[-20.194, -11.313]	Yes

Vehicle ownership	Own or lease	No	16.904	[15.170, 18.639]	Yes
Navigation app usage	A few times a week ≤	Once a week ≥	20.116	[18.587, 21.644]	Yes

Appendix C. The CIs of the difference between each subgroup for roundabouts

Subgroup	**Subgroups**		**Difference in trade-off**	**CI of difference**	**Significant**
	1	**2**			
Age	24 ≤	25 ≥	-4.399	[-4.601, -4.197]	Yes
Gender	Male	Female	2.343	[2.100, 2.586]	Yes
Educational level	2-year degree ≤	4-year degree ≥	-2.080	[-2.281, -1.879]	Yes
Personal situation	Student	Other	-0.246	[-0.625, 0.133]	No
Annual income	€20.000 <	€20.000 ≥	-1.769	[-2.016, -1.522]	Yes
Household size	1 and 2	3 ≥	0.336	[0.131, 0.540]	Yes
Driving experience	5 years ≤	6 years ≥	-2.559	[-2.797, -2.321]	Yes
Driving frequency	A few times a week ≤	Once a week ≥	-0.388	[-0.600, -0.175]	Yes
Vehicle type driven usually	Petrol	Other	6.433	[6.194, 6.673]	Yes
Vehicle ownership	Own or lease	No	0.505	[0.297, 0.714]	Yes
Navigation app usage	A few times a week ≤	Once a week ≥	1.525	[1.272, 1.778]	Yes

Appendix D. The CIs of the difference between each subgroup for highway

Subgroup	**Subgroups**		**Difference in trade-off**	**CI of difference**	**Significant**
	1	**2**			
Age	24 ≤	25 ≥	-24.875	[-27.536, -22.214]	Yes
Gender	Male	Female	-18.240	[-20.632, -15.848]	Yes
Educational level	2-year degree ≤	4-year degree ≥	26.000	[23.606, 28.395]	Yes
Personal situation	Student	Other	2.052	[-1.221, 5.325]	No
Annual income	€20.000 <	€20.000 ≥	-12.372	[-14.599, -10.145]	Yes
Household size	1 and 2	3 ≥	7.335	[4.781, 9.890]	Yes
Driving experience	5 years ≤	6 years ≥	-3.996	[-6.546, -1.445]	Yes
Driving frequency	A few times a week ≤	Once a week ≥	-41.131	[-43.719, -38.542]	Yes
Vehicle type driven usually	Petrol	Other	3.864	[0.944, 6.783]	Yes
Vehicle ownership	Own or lease	No	45.963	[42.928, 48.997]	Yes

Navigation app usage	A few times a week ≤	Once a week ≥	-11,562	[-14.127, -8.997]	Yes

Appendix E. The CIs of the difference between each subgroup for stations

Subgroup	**Subgroups**		**Difference in trade-off**	**CI of difference**	**Significant**
	1	**2**			
Age	24 ≤	25 ≥	0.736	[0.475, 0.996]	Yes
Gender	Male	Female	2.972	[2.663, 3.281]	Yes
Educational level	2-year degree ≤	4-year degree ≥	-0.786	[-1.105, -0.466]	Yes
Personal situation	Student	Other	-0.361	[-0.761, 0.039]	No
Annual income	€20.000 <	€20.000 ≥	-0.455	[-0.813, -0.097]	Yes
Household size	1 and 2	3 ≥	2.184	[1.889, 2.478]	Yes
Driving experience	5 years ≤	6 years ≥	-1.031	[-1.347, -0.714]	Yes
Driving frequency	A few times a week ≤	Once a week ≥	-3.578	[-3.907, -3.249]	Yes
Vehicle type driven usually	Petrol	Other	2.163	[1.883, 2.444]	Yes
Vehicle ownership	Own or lease	No	1,414	[1.045, 1.782]	Yes
Navigation app usage	A few times a week ≤	Once a week ≥	-3.445	[-3.756, -3.135]	Yes

Table F. The CIs of the difference between each subgroup for scenic route