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DOI
10.1016/j.trd.2025.104772

Publication date
2025

Document Version
Final published version

Published in
Transportation Research Part D: Transport and Environment

Transportation Research Part D 145 (2025) 104772

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Behavioral impact of range anxiety and unlock fees on shared electric-moped usage

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ARTICLE INFO

Keywords:
Electric moped sharing systems
Shared micromobility
Range anxiety
Pricing
Hybrid choice model
Stated preferences

ABSTRACT

The evolving field of electric moped sharing systems is shaped by various determinants influencing user preferences, including range anxiety, pricing strategies, and regulatory changes. Utilizing a stated preference approach with a hybrid choice model, this research explores how these factors, along with attitudinal constructs, impact user decisions. The findings reveal that remaining driving range plays a critical role, with significant individual variability in its sensitivity, while perceived range anxiety did not significantly influence choices. Recent changes in helmet regulations have shifted preferences towards faster vehicles. Furthermore, dynamic pricing strategies, such as adjusting ride or unlock fees, can incentivize the use of less desirable vehicles with lower battery range or aid in user-based relocation. Nevertheless, low-range vehicles are less likely to be chosen, even with incentives. These insights provide valuable guidance for operators of electric moped sharing system to improve fleet management and optimize user satisfaction through strategic pricing and battery management.

1. Introduction

As urban areas face growing challenges such as traffic congestion, pollution, and the environmental impact of private car ownership, shared electric mopeds (e-mopeds) emerge as a promising solution (Gössling, 2020). These systems can reduce private car use, ease congestion, and lower both noise and greenhouse gas emissions, contributing to more sustainable and livable cities (Shaheen, 2019). The free-floating type of shared e-mopeds (EMSS) have gained considerable popularity by offering users the flexibility of one-way transportation. However, this flexibility can lead to an imbalanced distribution of e-mopeds due to mismatches between supply and demand in both time and location (Ataç et al., 2021). Consequently, the system may experience underutilization in low-demand areas and undersupply in high-demand areas. To address this challenge, various strategies can be employed from both supply-side and demand-side perspectives. Supply-side strategies, namely operator-based relocation, can be costly due to logistics and staff deployment expenses. Also, frequent operator-based relocation strategy have adverse environmental impact (Reis et al., 2023). On the other hand, demand-side management strategies, specifically user-based relocation, may effectively mitigate this issue by offering (monetary) incentives to users for picking up vehicles with less desirable attributes (Angelopoulos et al., 2018; Pfrommer et al., 2014). The potential effectiveness of user-based relocation and overall service level enhancement relies on understanding users' preferences for individual e-mopeds, what they prioritize, and how to ensure the systems remain efficient, user-friendly, and

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https://doi.org/10.1016/j.trd.2025.104772
Received 7 November 2024; Received in revised form 20 April 2025; Accepted 20 April 2025

Available online 19 May 2025

accessible (Arbeláez Vélez, 2024). Therefore, it is crucial for EMSS providers to identify key factors affecting users' choices and the trade-offs they make between these factors.

Studies have identified various factors affecting users' preferences towards individual e-moped usage, including pricing strategies and walking distance to access an e-moped (Chen et al., 2023; Loudon et al., 2023; Hoobroeckx et al., 2023), users' socio-demographic information (van Kuijk et al., 2022), and behavioral determinants (Eccarius and Lu, 2020). Previous studies on vehicle characteristics have mainly concentrated on either pricing strategies or their trade-offs with walking distances, often overlooking the crucial aspect of vehicle power level, an integral part of electric mobility systems. The understudied factor for shared electric vehicle services is the phenomenon of "range anxiety", the concern that the battery may deplete before reaching the destination or a charging station (Nilsson, 2014; Birrell et al., 2014). Range anxiety can be understood from two perspectives: objective perception, which refers to the trade-off between the vehicle's remaining driving range and the trip distance, and attitudinal perception, reflecting how a user's subjective experience and perceived stress in critical range situations influence their behavior (Nazari et al., 2023; Shrestha et al., 2022). While most research on range anxiety has focused on privately owned electric vehicles (BEVs), its effects on shared mobility services remain underexplored. Compared to privately owned vehicles, shared micromobility systems such as e-mopeds and e-bikes add additional layers of complexity that may heighten range anxiety. Factors such as diverse vehicle types, limited user experience, insufficient information on routes or battery levels, and the inability to initiate charging can amplify user concerns. Consequently, users may avoid vehicles with lower battery levels, even when the remaining driving range is sufficient for their trip. This perception can create inefficiencies for operators and reduce the perceived availability of vehicles.

Study by (Loudon et al., 2023) has shown that individuals with prior experience using shared mopeds value e-moped attributes differently compared to those without such experience. In this study, we examine prior moped usage as a latent variable alongside subjective range anxiety. Additionally, new regulations have shown an impact on user preferences (Gössling, 2020). With the introduction of helmet regulations for e-mopeds in the Netherlands (commenced on January 2023), helmet use is mandatory for all types of e-mopeds, whereas previously, helmets were only required for faster vehicle types (Rijksoverheid, 2022). These regulatory changes are expected to affect user behavior and preferences, emphasizing the need to consider both attitudinal factors and external regulations in understanding the user's preferences towards individual e-mopeds.

This study investigates the factors influencing individual vehicle choice in EMSS, with a particular emphasis on vehicle battery level and the trade-offs between unlock fees, per-minute ride fees, and walking time required to access an e-moped. Utilizing a Hybrid Choice Modeling approach, we explore the impact of range anxiety in EMSS on user preferences, addressing both the objective remaining driving range and the attitudinal factors that influence behavior in critical range situations. Additionally, this study examines the impact of previous usage and regulatory changes to have a comprehensive view of user preferences. These areas have not been extensively covered in existing literature, highlighting the novelty and relevance of our analysis.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 describes the design of the stated preference experiment, the survey design, and the data collection process. The methodology for the choice modeling framework and its application are described in Section 4. The modeling results are presented and discussed in Section 5, followed by the model application in Section 6. Section 7 discusses management insights for EMSS providers, along with limitations and suggestions for future research. Finally, the paper concludes in Section 8.

2. Literature review

Next to other mobility sharing modes, shared e-moped services have emerged over the last decade, with their uptake accelerating significantly in recent years (Aguilera-García et al., 2020). EMSS currently operate fleets of free-floating e-mopeds that can be selected, unlocked, and locked via an app, charging users on a per-minute basis along with a fixed unlock fee. Recent studies show that adoption of e-moped sharing services is more prevalent among specific socio-demographic groups, including younger to middle-aged adults, males, highly educated individuals, and those with higher incomes (Aguilera-García et al., 2020; Vega-Gonzalo et al., 2024). Also, users with prior experience using EMSS are more likely to continue utilizing these services compared to those without such experience (Chen et al., 2023). While some factors driving EMSS adoption and usage have been identified, a more comprehensive understanding is necessary to fully capture the complexities involved.

Understanding main drivers of e-moped usage is essential for addressing spatial–temporal imbalances caused by uneven demand patterns through user-based relocation strategies. Several studies have demonstrated the potential of user-based relocation strategies in shared micromobility systems (Pfrommer et al., 2014; Neijmeijer et al., 2020). Two main factors determining users' willingness to participate in relocation strategies are identified in the literature: the willingness to walk for a prolonged period and the corresponding reduction in ride fees (Wang and Wang, 2021). Neijmeijer et al. (2020) conducted the first case study applying a dynamic pricing strategy in a free-floating e-moped sharing system, finding that even minor price deviations can effectively alter travel patterns. However, their analysis was limited to aggregate system performance metrics, overlooking individual behaviors and vehicle characteristics. Hoobroeckx et al. (2023) utilized Multinomial Logit models to examine the individual users' trade-offs between per-minute ride fees and walking distance based on stated preference survey data from the Netherlands. Their findings indicate that users require a reduction of €0.02 per minute in ride fees for each additional minute of walking to access a vehicle. Also, Chen et al. (2023) explored individual preferences in e-moped sharing by incorporating latent variables (advocacy for the service, hedonic motivation, and attitudes towards the service), capturing a better interpretation of user preferences in Taiwan. While these studies provide valuable insights into understanding of users preferences of EMSS, they do not account for vehicle battery levels—an integral attribute of electric mobility systems that influences both system efficiency and user decision-making.

Integrating vehicle-specific characteristics with user behavior could provide a more comprehensive understanding of the dynamics within EMSS and enhance the effectiveness of user-based relocation strategies.

Subjective Range anxiety captures how personal attitudes and anxiety related to low battery levels influence the likelihood of choosing an e-moped, providing deeper insights into user behavior, preferences, and potential barriers to adoption (Vij and Walker, 2016). While range anxiety has been extensively studied in battery electric vehicles (BEVs), it remains underexplored in shared micromobility systems. Research on BEVs, such as studies by Rauh et al. (2015) and Franke et al. (2015), identified the available range safety buffer as a key factor influencing range anxiety. From this framework, two critical factors emerge that influence user preferences in situations of limited range: the remaining objective battery range (actual distance the vehicle can cover) and the subjective point of range anxiety (stress threshold based on perceived range insufficiency). These factors are crucial in shaping user behavior and satisfaction in low-range scenarios. In shared micromobility systems, range anxiety may be triggered at higher remaining driving ranges compared to BEVs due to increased uncertainties and users' limited experience with shared vehicles in critical range situations. Key mitigation strategies include reducing uncertainties and providing comprehensive information (Rainieri et al., 2023). Furthermore, the trade-offs faced by users in shared electric mobility systems differ from those in privately owned BEVs. In BEVs, trade-offs typically involve route choice and charging infrastructure availability, whereas in shared systems, users can opt for vehicles with higher remaining driving ranges, disregarding those perceived as having insufficient range. These distinctions underscore the necessity to study critical range situations in shared electric mobility systems, focusing on both objective factors like remaining driving range and subjective factors such as perceived range anxiety.

Despite the valuable insights provided by existing studies on shared e-moped adoption, there remains a lack of comprehensive assessment regarding vehicle battery levels, service attributes – including both unlock and per-minute ride fees – as well as users' attitudes (such as range anxiety and previous system usage) and regulatory changes influencing usage behavior. By integrating these factors, this study aims to capture unobserved heterogeneity, improve model estimation performance, and enhance behavioral interpretation (Abou-Zeid and Ben-Akiva, 2024). Utilizing a Hybrid Choice Model, this research explores the interplay of these attitudinal factors, aiming to provide a more comprehensive understanding of the user's preference for individual e-moped usage in the EMSS.

3. Survey design and data collection

This section provides a comprehensive overview of the survey and data collection process. The final survey questionnaire consists of two parts: The stated preference choice experiment and questions about the socio-demographic profiles of the users, as well as indicator questions related to latent variables. These components are explained in the following. Additionally, the data collection process is described, outlining the methodology used to gather responses and ensure the validity of the data.

3.1. Stated preference experiment

A stated preference (SP) approach is selected because it allows the simulation of decision making by presenting respondents with hypothetical but realistic scenarios (Louviere et al., 2000). The key components of the SP experiment are outlined here, including the context of the survey, the attributes, their respective levels, and finally the process of generating the choice sets.

3.1.1. Context of the trip

The choice scenarios are designed within a fixed context to create critical range situations. As trip motive, running an errand is because such trips are typically occasional and time-sensitive, unlike daily commutes or leisurely trips (Loudon et al., 2023). A 5-km travel distance is chosen based on Hoobroeckx et al. (2023), which found that trips up to 5 km increase the utility of EMSS use, with the 90th percentile of trips being under 7.5 km and the average around 4 km. This translates to an approximate riding time of 15 min. This fixed distance emphasizes the importance of remaining driving range while still reflecting typical EMSS trip lengths. Weather conditions were standardized to neutral values (17 °C, cloudy and dry) to minimize their influence.

3.1.2. Attributes and attribute levels

In the stated preference experiment, five key vehicle attributes were considered: walking distance to the vehicle in minutes, unlock fee in €, ride fee in € per minute, remaining driving (that represents remaining battery level of the e-moped) range in kilometers, and e-moped type (25 km/h or 45 km/h). These attributes were chosen as they are the main factors displayed to users on the app interfaces of the EMSS providers. However, it is important to note that the remaining driving range has previously not been included in EMSS literature. The study therefore aims to explore the role that this attribute could play in influencing user preferences, particularly in critical range situations. Table 1 indicates a complete list of attributes, their attribute levels, and the corresponding indicator for the estimation.

The attribute levels are determined based on various sources, including current market situations and previous research. The levels of walking distance are derived from the data collected by Hoobroeckx et al. (2023), who report that the 90th percentile of walking distances is below 550 m. Assuming an average walking speed of 4 km/h, this translates to just over 8 min of walking time. Including some buffers, the walking times for this experiment range from 1 to 10 min. The unlock fee, ride fee, and vehicle types reflect the current market situation of EMSS providers, with at least one level above and below the current market situation. The levels for the remaining driving range are chosen to confront participants with critical range situations, providing a realistic context for the experiment. Inspired by the framework by Franke et al. (2015), which distinguishes between the competent, performant,

Table 1
Attributes and Attribute Levels for the stated preference experiment.

Attribute	Attribute levels	Parameter indicator
Walking distance in minutes	1, 4, 7, 10	$b_{Distance}$
Unlock fee in €	0.5, 1, 1.5, 2	$b_{UnlockFee}$
Ride fee in €/minute	0.27, 0.30, 0.33, 0.36	$b_{RideFee}$
Remaining driving range in km	5, 8, 11, 14	$b_{Battery}$
Vehicle type (dummy coded)	25 km/h (1), 45 km/h (0)	$b_{VehicleType}$

and comfortable ranges, we defined the lowest level to represent the trip distance, analogous to the competent range, while the additional levels incorporate progressively larger buffers, reflecting a progression towards stress-free (comfortable) conditions. As no prior research has been conducted on the influence of critical range situations, a broad range of remaining battery levels is selected, extending up to nearly three times the required trip length. It is assumed that all levels of remaining driving range still fall within the category of critical range situations. For the remainder of this paper, all discussions on critical range situations refer to this definition. Additional specific attributes introduced in this study include the unlock fee and the remaining driving range, both critical to understanding user preferences in EMSS by reflecting the current market situation and practical challenges faced by users.

3.1.3. Generation of choice sets

The construction of the choice sets in this SP experiment is designed to capture the key vehicle attributes. The survey includes a total of 16 choice sets, each presenting 2 e-moped alternatives to the participants, and one option not to use the sharing service (opt-out option). All attributes varied between the choice sets to ensure a comprehensive analysis of user preferences. Fig. 1 represents an example choice set.

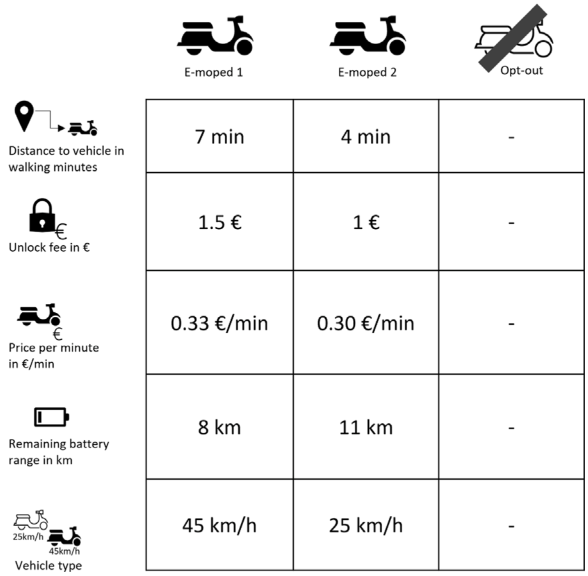


Fig. 1. Example Choice Set from Survey.

A D-efficient design is used to construct the choice sets using Ngene software (ChoiceMetrics, 2012), with priors from the pilot survey to enhance statistical efficiency. Notably, the D-efficient design reduces the minimum required sample size compared to a traditional random orthogonal design, enabling the reliable estimation of all parameters at statistically significant levels (Rose and Bliemer, 2013). The survey is divided into four blocks of four choice sets, meaning each participant answers four choice sets. The blocks are randomly presented to participants, ensuring that all four blocks are equally distributed. The choice sets are generated twice: initially for the pilot survey and then revised based on the pilot results for the main data collection. This iterative process refines the choice sets, ensuring they are both realistic and effective in capturing the necessary data to analyze user preferences. The final construction of the choice sets achieves a D-error of 0.214.

To ensure the relevance of the framework to real-world cases, certain constraints are applied. In particular, the distribution of the remaining driving range attribute is adjusted to mitigate the dominance of certain alternatives (Walker et al., 2018), with the 5 km level appearing more frequently and the 14 km level less frequently in the choice set. The vehicle type attribute is dummy-coded for analysis, where 1 represents the 25 km/h version and 0 represents the 45 km/h version. Including an opt-out option in the SP experiment increases its explanatory power by enhancing the realism and validity of the decision-making process (Louviere et al., 2000). The opt-out option captures situations where respondents might choose not to make a decision, providing valuable insights into their preferences and allowing for the modeling of latent variables or socio-demographic influences on EMSS use (Dhar and Simonson, 2003).

3.2. Explanatory variables

To enhance the explanatory power of the stated preference experiment, two latent variables are included in the survey: respondents' attitudes towards EMSS and their perception of range anxiety, representing the subjective influence of critical range situations on user preferences. Incorporating these latent constructs allows us to measure the impact of psychological factors on decision-making beyond observable attributes like cost or remaining driving range. For example, attitudes towards EMSS reveal how positive or negative perceptions affect willingness to use them, consistent with studies conducted in Spain by Aguilera-García et al. (2020) and Aguilera-García et al. (2021). Similarly, adding an attitudinal construct to better understand the influence of range anxiety, beyond the objective remaining driving range attribute, enriches our understanding of how critical range situations affect user preferences. The latent variables are measured using multiple questions, with responses recorded on a 5-point Likert scale. A complete overview of the survey questions and descriptive statistics is presented in Table 2 in Section 5.1. Although the target respondents for this study are individuals above 18 years of age with a valid driving license, a variety of socio-demographic characteristics and information about prior use are also collected and incorporated into the modeling process. These socio-demographic attributes, providing deeper insights into respondents' backgrounds and preferences, are detailed in Section 5.1.

3.3. Data collection process

The survey focuses on the Netherlands without targeting any specific region, ensuring broad applicability of the findings. The target respondents are EMSS users and non-users aged 18 and older with a valid driver's license, capturing a wide range of user preferences. A pilot survey is conducted prior to the main data collection to ensure clarity and enhance the robustness of the choice sets. The reliability of the latent variable indicators is also tested based on the pilot results and adjusted accordingly. The final survey is launched on May 27, 2024, and remains open until July 24, 2024. The distribution strategy involves three main channels: social media platforms (e.g., LinkedIn), mailing lists, and flyer handouts at micromobility hubs.

4. Choice modeling framework

We adopt a hybrid choice model (HCM) or integrated choice and latent variable (ICLV) model with random parameter estimation. This model allows us to simultaneously investigate the effects of vehicle attributes, socio-demographic factors, and latent attitudes on the intention to use EMSS (Danthurebandara et al., 2013). In the next section the underlying assumptions and structure of the HCM are explained.

4.1. Hybrid choice model with random parameter estimation

The HCM enhances traditional discrete choice models by integrating latent variables and socio-demographic factors, offering a more comprehensive understanding of individual preferences and behaviors (Ben-Akiva et al., 2002). A key advantage of HCM is its ability to capture unobservable factors, such as attitudes and perceptions, through psychometric data and structural equation modeling. This allows for a nuanced analysis of how these latent traits, alongside observed factors such as vehicle attributes, shape decision-making (Bolduc and Daziano, 2010).

The choice probability for the HCM is based on utility maximization theory, and the formula is given by:

$$P_{ij} = \int \frac{e^{V_{ij}(\beta,\eta)}}{\sum_{k\in C_i} e^{V_{ik}(\beta,\eta)}} f(\beta,\eta \mid \theta)\, d\beta\, d\eta \tag{1}$$

where P_{ij} is the choice probability of alternative j by individual i, C_i is the set of all alternatives available to individual i, β represents the vector of random parameters, η represents the vector of latent variables, and $f(\beta,\eta \mid \theta)$ is the joint density function of β and η with parameters θ.

Two latent variables for attitudes towards e-mopeds and perception of range anxiety were included in the model. In addition to the latent variables, the model includes significant random parameters identified through an iterative backward estimation, retaining only those vehicle attributes with 95% confidence level significance. Fig. 2 represents the complete conceptual model of the HCM.

The utility functions for the two e-moped alternatives are identical and defined in Eq. (2). The utility for the opt-out option is set to 0 to represent the baseline utility as described in Eq. (3):

$$\begin{aligned} V_{e\_Moped} = {} & ASC_{MSS} + b_{Distance} \cdot Distance + b_{UnlockFee} \cdot LockFee + b_{RideFee} \cdot RideFee + \\ & b_{Battery} \cdot RemainingRange + b_{VehicleType} \cdot VehicleType + \quad b_{previous} \cdot PreviousUse + \\ & b_{bike} \cdot Bike + \quad b_{low\_income} \cdot IncomeLow + \quad b_{alone} \cdot LivingAlone + \quad b_{shared} \cdot LivingShared + \\ & \eta_{emop} \cdot Attitude\_E\_mop + \quad \eta_{rangaxi} \cdot Perception\_range\_anxiety + \\ & b_{interaction} \cdot (RemainingRange \cdot Perception\_range\_anxiety) \end{aligned} \tag{2}$$

$$V_{Opt\_Out} = 0 \tag{3}$$

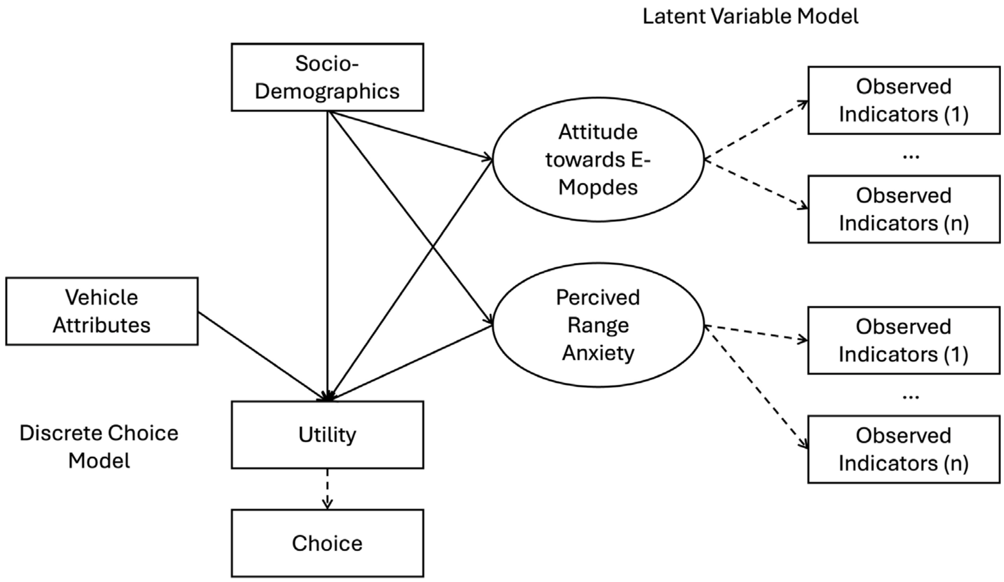


Fig. 2. Conceptual model HCM for e-moped usage.

The socio-demographic variables are incorporated directly into the utility function and are also linked to latent variables through the structural model. This allows for the estimation of both the direct and indirect effects of socio-demographic variables on choices, as mediated through latent variables. Additionally, the utility function incorporates an interaction term between the remaining driving range and the latent variable of range anxiety, allowing us to explore whether the subjective experience of range anxiety influences the perception of the objective remaining driving range of the e-moped.

The latent variable is represented through both a structural model and a measurement model. The structural model connects the latent variable to the observed socio-demographic variables, as shown in Eq. (4), while the measurement model relates the indicator variables to the latent variable, as described in Eq. (5).

$$\eta_{il} = \gamma_l \cdot X_{il} + \epsilon_{il} \tag{4}$$

Where, γ_l represents the coefficients for the socio-demographic variables X_{il} of an individual i and η_{il} is the lth latent variable (e.g., attitudes towards e-mopeds, perceived range anxiety) and ϵ_{il} is the disturbance term associated with the latent variable η_{il}.

$$I_{iq} = \zeta_q \cdot \eta_l + \delta_{iq} \tag{5}$$

Where I_{iq} is the qth indicator, representing survey questions measuring attitudes towards e-mopeds or perceived range anxiety. ζ_q is the loading factor, indicating the strength of the relationship between the latent variable η_l and the indicator I_{iq} and δ_{iq} is the random error term for indicator I_{iq}, assumed to follow a standard normal distribution.

The HCM was estimated using 5000 Halton draws for the random parameters and the error terms of the latent variables to ensure efficient and accurate integration over the random components. Unlike pseudo-random numbers, which are completely random, Halton sequences are designed to cover the integration space more evenly. This even distribution helps reduce the simulation error associated with maximum simulated likelihood estimation (Zeng, 2016). As an estimation software, the Apollo package in R was used (Hess and Palma, 2019a).

4.2. Model application framework

To further contextualize the results, we employ two methods: the calculation of Willingness-to-Pay (WTP) indicators and a scenario analysis to assess market shares for different vehicle attribute values.

4.2.1. WTP and elasticity indicators

We calculated WTP indicators for all non-price vehicle attributes (walking distance, remaining driving range, and vehicle type) to quantify the trade-offs users are willing to make between various vehicle features. Traditionally, WTP indicators are calculated by dividing the estimated coefficient of a non-price attribute by the coefficient of a price attribute. However, in our model, we have two price components: the unlock fee and the per-minute ride fee, resulting in two distinct sets of WTP indicators. For example, the WTP for a reduction in walking time based on the unlock fee can be calculated using the formula:

$$WTP_{\text{Distance, UnlockFee}} = \frac{b_{\text{Distance}}}{b_{\text{UnlockFee}}} \tag{6}$$

where b_{Distance} is the estimated coefficient for the walking distance to access the e-moped, and $b_{\text{UnlockFee}}$ is the estimated coefficient for the unlock fee. Since both coefficients are fixed parameters in our model, this WTP is a single value. However, for attributes with random coefficients, such as the per-minute ride fee and remaining driving range, the WTP indicators are calculated using distributions. For instance, the WTP for additional battery range (driving range) based on the per-minute ride fee is determined by:

$$WTP_{\text{Battery, RideFee}} = \frac{b_{\text{Battery}}}{b_{\text{RideFee}}} \tag{7}$$

In this case, b_{Battery} and b_{RideFee} are random parameters that follow specific distributions. To calculate the WTP, we derive the distribution of their ratio as shown in Eq. (7), which represents the range of WTP values across different individuals. This approach captures the variability in user sensitivity to these attributes and reflects the heterogeneity in the population, providing a more comprehensive understanding of user preferences.

To understand which variable influences the likelihood of choosing an e-moped, in addition to the WTP indicators, we also calculated elasticities for various variables (denoted as X_k). The responsiveness of e-moped demand to changes in these variables is captured by elasticities, which indicate the magnitude of behavioral responses. Given that choice probabilities in our model are obtained through simulation, the arc elasticity approach was adopted as a more practical method for approximating aggregate elasticities, particularly in response to small changes in variable values (Train, 2009). Elasticities were computed for a 1% increase in unlock fees, ride fees, and walking distance using Eq. (8) (Hess and Palma, 2019b). The results of these analyses are discussed in Section 6.1.

$$E_k = \frac{\log\left(\sum_i P'_{ij}\right) - \log\left(\sum_i P_{ij}\right)}{\log(1.01)} \tag{8}$$

where E_k is the elasticity for variable X_k. P_{ij} and P'_{ij} represent the base choice probabilities of alternative j for individual i and the choice probabilities after increasing X_k by 1%, respectively. $\log(1.01)$ ensures that the elasticity corresponds to a 1% increase in X_k.

4.2.2. Scenario analysis

For the scenario analysis, we utilize the choice probability function of the HCM to explore how variations in vehicle attributes affect user choices. Unlike typical scenario analyses that use fixed values for each scenario, this approach examined a range of attribute values to capture their dynamic influence on the likelihood of EMSS usage. Heatmap figures in Section 6.2, are generated to visually represent how changes in attributes like walking distance, and remaining driving range, compared to the price attributes, impact the probability of choosing EMSS. Since the two e-moped alternatives have identical utilities in this analysis, we treated them as a single alternative, focusing on the decision to choose any e-moped versus opting out. This simplification allows us to concentrate on how varying vehicle attributes influence the overall likelihood of choosing EMSS. For the scenario analysis, typically, the mean of the random parameters is used as a fixed value when calculating probabilities. However, to ensure realism, we derived these values through a Monte Carlo simulation and then averaged the probabilities across all individuals to obtain the overall likelihood of choosing e-mopeds. The results of this analysis are presented in Section 6.2.

5. Results

The following sections provide an overview of the results derived from the choice model and survey. First, the descriptive statistics of the respondents are presented. Then, as discussed in the methodology (Section 4), the HCM with a random parameter approach and the derived indicators are discussed.

5.1. Descriptive statistics

This section provides a brief overview of the characteristics of the respondents. Of the 154 respondents, 133 completed the entire survey and met the criteria for the SP experiment, which required participants to be over 18 years old and possess a valid driving license. This resulted in a total of 532 observations collected.

The distribution of users and non-users was nearly equal, with 49.6% of respondents being non-users, 7.5% being one-time users, 36% having used EMSS a few times, and 6.9% being frequent users. Age-wise, the sample is skewed towards younger individuals, with 66% of respondents under 30 and 86% under 40. Although this may present bias, it aligns with the demographic of the primary user of EMSS, as reported by numerous studies, such as Aguilera-García et al. (2020). The gender distribution was slightly biased towards male respondents, which comprised 58% of the sample, while female respondents accounted for 40%. An additional 2% of respondents selected a third gender or preferred not to disclose their gender. The majority of the respondents were employed (57%) or students (33%), with smaller percentages being self-employed, looking for work, or retired. For the income distribution, respondents can be categorized into three income groups: low, middle and high. Low-income respondents, earning up to €2000, make up 39.1% of the sample. The middle-income group, earning between €2000-4000, comprises 42.8% of the respondents, while the high-income group, earning above €4000, represents 16.8% of the sample. The living situations were also categorized into three groups: living alone, living with a partner, and living in shared flats. Those living alone made up 21.8% of the sample, while 46% lived with a partner, and 30.8% lived in shared flats. Regarding education levels, a substantial proportion of respondents had a high educational level: 57% had a master's degree or Ph.D., and another 36% had a bachelor's degree.

Compared to national averages in the Netherlands, our sample is younger, more educated, and exhibits a slight male bias. Nevertheless, it closely mirrors the demographic profile of the e-scooter user group in the Netherlands as reported by Statista (2024), which indicates that nearly 90% of users are under 44 years old and that the gender split is approximately 58.3% male to 41.7% female. In terms of income, the sample was more skewed towards low to middle incomes, with 39.1% earning up to €2000 and 42.8% earning between €2000-4000, while the national income distribution has a more balanced spread across different brackets (CBS, 2022). These differences, particularly in age and education, are expected as younger, more educated individuals tend to be early adopters of new mobility technologies like EMSS (Aguilera-García et al., 2020).

The latent variables "Attitude towards EMSS" and "Perceived Range Anxiety" were designed to capture the underlying psychological factors that influence user preferences in vehicle choice within EMSS. Each latent variable was measured using a set of four indicators. For "Attitude Towards EMSS", the indicators included statements about e-mopeds being a good addition to urban transport, their convenience, their potential to reduce private vehicle use, and their ease of access. Meanwhile, "Perceived Range Anxiety" was assessed through indicators focusing on concerns about the remaining driving range, anxiety due to low battery levels, users' estimations of trip length, and preferences for higher range to avoid stress. Respondents rated these indicators on a 5-point Likert scale ranging from "Strongly disagree" to "Strongly agree". An overview of the descriptive statistics for the latent variables can be seen in Table 2.

Table 2
Descriptive Statistics and Reliability for Latent Variable Indicators.

No	Indicator description			Frequency distribution (%)				
	Attitude towards EMSS ($\alpha = 0.735$)	Mean	SD	1	2	3	4	5
1	E-Moped Sharing Systems are a good addition to the various modes of transport available in urban regions	3.95	0.84	0.8	3.8	13.5	56.4	25.6
2	E-Moped Sharing Systems are a convenient and practical mode of transport in urban regions	3.92	0.84	0.8	3.8	13.5	56.4	25.6
3	E-Moped Sharing Systems can reduce your need for a private vehicle/car	3.51	1.18	3.8	11.3	18.8	41.4	24.8
4	E-Moped Sharing Systems are easy to use/access	3.79	0.82	0.8	8.3	15.8	55.6	19.5
	Perceived Range Anxiety ($\alpha = 0.658$)							
5	When choosing an e-moped, the remaining driving range of the vehicle is important to me.	3.81	0.90	2.3	6.0	14.3	55.6	21.8
6	I experience anxiety while using an e-moped from a sharing system due to low remaining driving range.	3.26	1.03	3.8	20.3	30.8	28.6	16.5
7	I do have an approximation of the trip length when taking an e-moped.	3.68	0.92	1.5	8.3	22.6	47.4	20.3
8	To avoid anxiety or stress, I would choose an e-moped with significantly more range than necessary.	3.59	1.10	3.0	11.3	21.1	44.4	20.3

The descriptive statistics for the latent variable indicators reveal several key insights. For "Attitude Towards EMSS", the indicators generally show high mean values, particularly for Indicator numbers 1, 2, and 4. This suggests a favorable overall perception of e-mopeds among respondents. The reliability coefficient Cronbach alpha suggests good internal consistency with a value of 0.735. Cronbach's alpha values above 0.7 are generally considered acceptable for measuring the reliability of a latent variable (Gliem and Gliem, 2003). On the other hand, "Perceived Range Anxiety" indicators have more varied responses, as reflected by their wider range of mean values. The concern about remaining driving range (indicator number 6) shows a relatively high mean, indicating that it is a significant factor for many users. While the reported Cronbach alpha is slightly below the desired threshold of 0.7, when excluding indicator number 7, which has the least explanatory power for the latent variable, Cronbach's alpha increases to 0.8049, indicating strong reliability. This can be justified, as indicator number 7 has the lowest factor loading from the latent variable and is further not included in the final latent variable estimation, as it showed no significant influence on the variable (see Section 5.3).

5.2. Hybrid choice model

In the following, the results of the HCM are discussed and interpreted. With the utility of not using EMSS fixed at zero, an Alternative Specific Constant (ASC_{MSS}) was estimated representing the base utility of choosing EMSS. Furthermore, the model reveals how various socio-demographic factors and attitudes, such as range anxiety or perceptions of shared mobility, impact the likelihood of selecting EMSS. As discussed in Section 4 an iterative backward estimation process was adopted, only retaining significant socio-demographic variables and latent indicators as well as, testing for heterogeneity through a random coefficient distribution. The main estimates for the vehicle attributes, socio-demographics and latent variables are presented in Table 3. The full set of parameter estimates can be found in Appendix A. The following section will analyze and interpret these results to provide a comprehensive understanding of the model results and implications.

The parameters show high statistical significance, with all t-ratios surpassing the critical value of 1.96 are treated as final variables in the model. This threshold corresponds to the 95% confidence level. Thus allowing us to reject the null hypothesis that the

Table 3
Estimation results hybrid choice model.

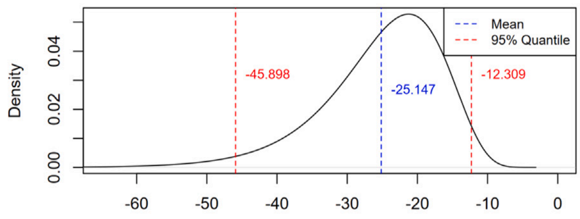
Model fit indicators				
Metric	Value			
LL(start)	−2421.42			
LL(final, whole model)	−1388.24			
BIC	3074.78			
Vehicle Attributes				
Parameter	Estimate	s.e.	t-ratio	p-value
ASC_{MSS}	10.514	1.786	5.8862	0.000
$b_{UnlockFee}$	−1.419	0.223	−6.343	0.000
$b_{VehicleType}$	−1.023	0.212	−4.830	0.000
$b_{Distance}$	−0.342	0.043	−7.969	0.000
Random Parameter	Estimate (s.d.)	s.e.	t-ratio	p-value
$b_{RideFee}$	−25.47 (8.948)	0.127	–	–
$b_{Battery}$	0.282 (0.079)	0.001	–	–
Socio-Demographic Estimates				
$b_{previous}$	−1.719	0.629	−2.731	0.005
b_{bike}	−2.212	1.107	−1.996	0.022
b_{alone}	1.212	0.461	2.628	0.005
b_{shared}	−0.864	0.441	−1.959	0.052
b_{low_income}	−1.18	0.471	−2.511	0.005
Latent Variable Parameter Estimates				
$\eta\_emop(LV1)$	0.830	0.304	2.723	0.003
$\gamma\_LV1 - previous$	0.829	0.217	3.810	0.000
$\gamma\_LV1 - nationalityDutch$	−0.340	0.166	−2.04	0.043
$\gamma\_LV1 - educationBachelor$	0.370	0.163	2.271	0.024
$\gamma\_LV1 - educationMaster$	−0.315	0.142	−2.223	0.027
$\eta\_rangaxi(LV2)$	−0.585	0.368	−1.597	0.112
$b_{interaction-battery*LV2}$	0.033	0.027	1.208	0.229

parameter mean effect is equal to zero. The alternative specific constant ASC_{MSS} for EMSS is positive. The value of ASC_{MSS} represents the systematic difference in utility between choosing the EMSS alternative and opting for the opt-out alternative when the EMSS attribute values are set to zero. This suggests a systematic preference for the EMSS option over the opt-out alternatives, independent of other model attributes. This is contrary to previous findings by Hoobroeckx et al. (2023) indicating a negative base utility for EMSS. This change may be explained by varying context attributes in the latter study presenting less favorable conditions to potential users.

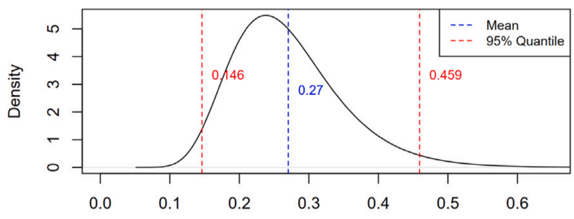
The newly introduced pricing parameter for the unlock fee ($b_{UnlockFee}$) showed the expected negative sign with an estimate of −1.41, indicating a general disutility for higher unlock fees. While this parameter is included for the first time in an SP experiment on EMSS in the Netherlands this is expected and in line with recent studies on micromobility (Ren et al., 2024), also reporting the negative influence of unlock fees on user preference. The parameter for the walking distance to a vehicle ($b_{Distance}$) also has its expected negative sign with an estimate of −0.34 indicating general disutility for longer walking distances.

The negative parameter for vehicle type ($b_{\text{VehicleType}}$) indicates a preference against the slower vehicle, which contrasts with the findings of Hoobroeckx et al. (2023). Their study identified the absence of a helmet requirement as a key factor influencing users' preference for the slower vehicle. Although the model in the current paper does not explicitly include a variable to capture the effect of helmet regulations, respondents were informed about the mandatory helmet regulations before completing the survey. Therefore, it is reasonable to assume that the regulation influenced their choices. The results suggest that the introduction of the helmet mandate may have shifted user preference towards faster vehicles by eliminating the previously available convenience of riding without a helmet, which applied specifically to slower e-mopeds. Furthermore, the remaining advantage of using bike paths with the slower vehicle does not appear to provide a sufficient incentive to outweigh the appeal of the faster alternative.

The two parameters that showed significant heterogeneity in the estimation are the second pricing parameter for the per-minute ride fee ($b_{RideFee}$) and the parameter for the remaining driving range ($b_{Battery}$). All other parameters have also been tested for heterogeneity but did not show significant variability. We assumed negative and positive log normal distribution for the per-minute ride fee and battery level respectively, based on empirical modeling practices grounded in their behavioral properties (Train, 2009). The parameter estimate for the ride fee ($b_{RideFee}$) shows a mean value of −25.147 with a standard deviation of 8.68. This results in the 95% quantile of the distribution between −45.89 and −12.30 (see Fig. 3(a)). While we can see a high influence of the ride fee on perceived user utility this factor varies greatly between individuals. The newly introduced parameter estimate for the remaining driving range ($b_{Battery}$) has a mean value of 0.27 with a standard deviation of 0.08. This results in the 95% quantile of the distribution between 0.146 and 0.459 (see Fig. 3(b)). This suggests that higher battery levels generally increase the vehicle's utility, but there is substantial variability in how different users value this attribute. Some users may have a strong preference for higher battery levels, while others may be less concerned.



(a) Distribution of ride fee ($b_{ridefee}$)



(b) Distribution of remaining driving range ($b_{battery}$)

Fig. 3. Distributions of random parameter estimates.

5.3. Influence of latent variables and socio-demographics

The influence of socio-demographic characteristics showed significance in only 5 parameters. The "previous use" parameter unexpectedly had a negative sign, indicating that prior experience with EMSS negatively influences the likelihood of using it. This contrasts with findings from studies by Aguilera-García et al. (2020) and Alonso-González et al. (2021), which reported that previous use is one of the main factors driving EMSS adoption. Several factors could explain this counterintuitive result. One possible explanation lies in the specific context of this study, suggesting that the utility derived from previous EMSS use diminishes under certain operational conditions or constraints. Additionally, the nature of prior use – which was not explicitly captured in the survey – may have influenced respondents' choices. For instance, users who previously had a negative or inconvenient experience with EMSS may be less inclined to select it, thereby contributing to the observed negative effect. This observation is also supported by Egbue and Long (2012), demonstrating that adverse experiences, such as limited driving range and charging challenges, can reduce consumer preferences for adopting electric vehicles. In line with previous research (Hoobroeckx et al., 2023), bike ownership negatively influences EMSS usage, suggesting a significant overlap in the use patterns between bike trips and EMSS. Interestingly, respondents' living situations also impact EMSS usage. Living alone has a positive influence on EMSS adoption, while living in a shared flat negatively influences it, compared to living with a partner, which serves as the reference category. Lastly, lower income negatively impacts EMSS usage compared to higher incomes, while the medium income category did not show significance and was therefore excluded from the model. As discussed in the review of the literature of this study, the influence of higher income on EMSS adoption is not consistent within previous studies, sometimes driving adaptations, sometimes hindering it (Aguilera-García et al., 2020; Vega-Gonzalo et al., 2024). To summarize these findings within this stated preference context, users with high income, no previous use, and who live alone are most likely to use EMSS.

In the final HCM, three out of four indicators for both "Attitude towards EMSS" and "Perceived Range Anxiety" showed statistical significance, demonstrating the relevance of these latent variables in capturing user preferences. The parameter η_{emop} for "Attitude Towards EMSS" was estimated at 0.830 with a robust t-ratio of 2.723, indicating that a positive attitude towards EMSS increases the likelihood of choosing an EMSS over opting out. This suggests that users with favorable perceptions of e-mopeds are more likely to adopt EMSS, and is in line with previous studies like Chen et al. (2023) and Aguilera-García et al. (2021). Attitudes towards EMSS can be shaped by both socio-demographic factors and context-specific variables related to EMSS usage. Prior usage of EMSS positively influences attitudes, suggesting that previous experience indirectly enhances EMSS utility by fostering more favorable perceptions. However, as discussed earlier, its direct effect on utility was negative, which could be due to past adverse experiences while using EMSS. Additionally, Dutch nationals exhibited a relatively negative attitude towards EMSS compared to non-Dutch respondents.Education level also proved to be influencing the attitudes towards EMSS. Individuals with a bachelor's degree displayed a more positive attitude, whereas those holding a master's degree or higher demonstrated a comparatively negative perception. These findings underscore that socio-demographic factors not only have a direct impact on the utility of choosing EMSS but also exert an indirect influence by shaping latent attitudes, which in turn affect EMSS utility.

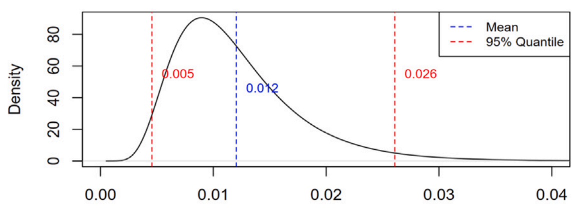
Conversely, the parameter η_{rangaxi} for "Perceived Range Anxiety" is estimated at −0.585 with a robust t-ratio of −1.59, indicating that it is not statistically significant at the 95% confidence level. However, we have reported it in the model to highlight the potential negative influence of range anxiety on EMSS adoption. Additionally, an interaction term between range anxiety and the remaining battery level was tested to examine whether users' level of anxiety about range influences their sensitivity to the actual remaining battery. The results indicate that this interaction is insignificant, suggesting that the effect of remaining battery level on the choice outcome does not vary with the user's level of range anxiety. In other words, individuals with high and low range anxiety respond similarly to variations in the remaining battery level when making their choices. Furthermore, previous research has shown that objective range indicators, such as the remaining driving range, are typically more decisive in user choices when both subjective and objective range considerations are present (Franke et al., 2016; Nazari et al., 2023), which could explain the insignificant interaction term.

6. Model application

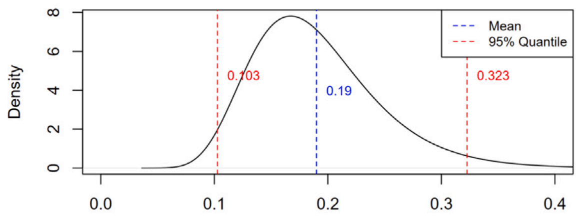
In this section, we contextualize the model findings by first examining the WTP indicators, which quantify the trade-offs between specific attributes. Next, we conduct a scenario analysis to explore how changes in key vehicle attributes influence decision-making and behavior, offering insights into the practical implications of the model.

6.1. Willingness-to-pay and elasticity indicators

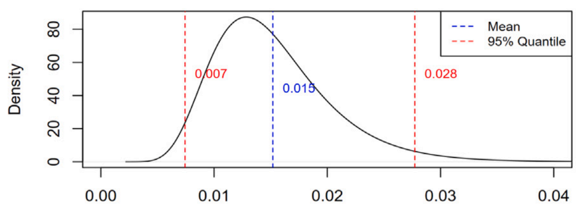
WTP indicators translate the parameter estimates into actionable insights, helping to inform operational decisions for EMSS operators. Since two random parameters were found to be significant, the WTP indicators are distributed according to the random parameter distributions. Fig. 4 provides an overview of all WTP indicators affected by at least one random parameter, while 4 displays the two remaining WTP indicators.



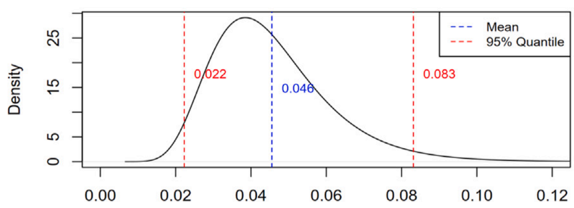
(a) Distribution of WTP for additional Battery (ride fee)



(b) Distribution of WTP for additional Battery (unlock fee)



(c) Distribution of WTP for a reduction in walking distance (ride fee)



(d) Distribution of WTP for a faster vehicle (ride fee)

Fig. 4. Distributions of WTP for various factors derived from Hybrid Choice Model.

Table 4
Willingness to Pay (WTP) for Various factors.

Description	Value	Unit
WTP for reduction in walking (unlock fee)	0.24	€ for 1 min
WTP for a faster vehicle (unlock fee)	0.72	€ for 45 km/h vehicle

The mean WTP for additional driving range based on the per-minute ride fee (see Fig. 4(a)) is €0.012/min for the ride fee, with a 95% quantile ranging from €0.005/min to €0.026/min. This suggests that users value the extra battery capacity, but their valuation varies significantly. For example, if a vehicle offers 3 km less range in a critical range situation, it must be on average €0.036 cheaper in per-minute ride fee. Although due to its heterogenity, this WTP indicator could range from a reduction of €0.015 to €0.078 per-minute ride fee. Regarding the unlock fee, the WTP for additional battery (see Fig. 4(b)) is €0.19, with a 95% quantile between €0.10 and €0.32. When comparing the mean reductions needed for the unlock fee and the per-minute ride fee on a 15 min trip (driving time of 15 min), the reduction in the unlock fee (€0.57) is slightly higher than the total reduction in the ride fee (€0.54).

The mean WTP for a one minute reduction in walking time is slightly lower than reported by Hoobroeckx et al. (2023), who found a reduction of €0.02/min in the ride fee for each additional minute of walking. In our model, the WTP for a reduction in walking time (see Fig. 4(c)) has a mean of €0.015/min, with the 95% quantile of the distribution ranging from €0.007/min to €0.028/min. For example, a e-moped located three minutes farther away must have an average reduction of €0.045/min of the ride fee to remain equally attractive. Due to the heterogeneity captured by the model, this WTP could vary widely, ranging from a reduction of only €0.021 up to €0.084 per-minute ride fee.

When assuming a trip duration as pictured in the context (driving time of 15 min), this results in a total ride fee reduction of approximately €0.68. For the unlock fee, a reduction of €0.24 is needed per extra walking minute. This WTP is not dependent on a random parameter but is based on two fixed estimates. In the same example, a total reduction of €0.72 is required for an additional three minutes of walking, again being slightly higher than the total influence of the ride fee parameter.

Lastly, the WTP for a faster vehicle is considered. The mean WTP for a faster vehicle based on the ride fee (see Fig. 4(d)) is €0.046/min, with a 95% quantile of the distribution between €0.022/min and €0.083/min. This quantifies the significant shift in preference, probably due to new helmet regulations (Rijksoverheid, 2022). In contrast to previous studies reporting a preference for the slower vehicle type, the current preference for the faster type is as strong as a three-minute reduction in walking time. For the unlock fee, a reduction of €0.72 is required to make the slower vehicle type equally attractive.

The WTP analysis provided insights into the trade-offs users are willing to make between different attributes of the EMSS system. Additionally, elasticity measures were calculated for various factors to assess how changes in attributes influence the probability of choosing an e-moped. Specifically, the percentage change in the probability of selecting an e-moped was estimated for a 1% increase in unlock fees, price per minute, and walking distance. A high elasticity value indicates that demand for EMSS is sensitive for that particular attribute; that is, a relatively small change in the attribute causes a relatively large change in the likelihood of choosing EMSS.

The results from the elasticity analysis indicate that a 1% increase in user fees, walking distance, and price per minute leads to a reduction in the demand for EMSS by 0.42%, 0.37%, and 1.76%, respectively, consistent with the expected negative sign of the elasticity values. Among these attributes, price per minute exhibits the highest elasticity, suggesting that increases in this attribute have the most significant impact on reducing the demand for EMSS. Economists classify elasticity values based on their relative magnitude: inelastic (absolute value less than 1), perfectly elastic (absolute value equal to 1), and elastic (absolute value greater than 1) (Oum and Yong, 1990). In this context, demand for EMSS is elastic with respect to the price per minute, while it is inelastic with respect to unlocking fees and walking distance.

In summary, the WTP and elasticity analyses reveal that all attributes included in the model significantly influence user preferences and the likelihood of choosing EMSS. These findings provide valuable insights for EMSS operators, which are discussed in detail in Section 7.

6.2. Scenario analysis

This section presents and discusses the results derived from the scenario analysis, as explained in Section 4.2.2. To examine how variations in non-price vehicle attributes affect price-related attributes, we first set the remaining variables to fixed values, aiming to represent the average respondent profile derived from the survey (see Section 5.1). These values provide a representative EMSS user profile, that explains the high likelihood of choosing EMSS in the scenarios. For random variables, rather than using their mean values as fixed inputs, we employed Monte Carlo simulation to generate values based on the estimated distributions from the model. This approach offers a more realistic representation by accounting for individual-level variation in the random parameters. The likelihood values for different scenarios were then obtained by averaging the choice probabilities across all respondents. It is important to note that the likelihood of choosing EMSS is also highly context-dependent, as described in Section 3.1.1. The SP experiment conditions – such as favorable weather, occasional trip patterns, and high service availability – create an environment that supports EMSS adoption. In the following subsections, we discuss how variations in vehicle attributes influence this likelihood.

6.2.1. Influence of remaining driving range on the likelihood of choosing EMSS

In this first scenario analysis we explore how the likelihood of choosing a shared e-moped changes solely based on varying the remaining driving range attribute. The results are illustrated in Fig. 5.

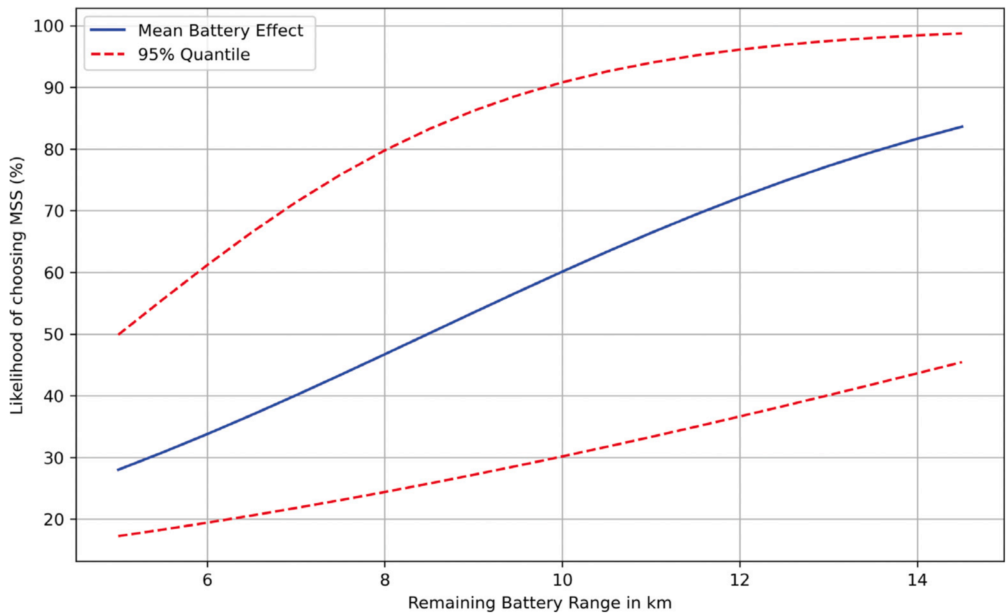


Fig. 5. Likelihood of Choosing EMSS based on varying remaining driving range levels.

All the other vehicle attributes remain fixed to reflect current market prices and average walking distance, i.e. a walking distance of 5 km, ride fee of €0.33 and a unlock fee of €1 utilizing a 25 km/h vehicle type. In this scenario, the random parameter for the remaining driving range is used, incorporating two curves that represent the lower and upper 95% quantiles of the distribution.

Fig. 5 shows the significant influence of the remaining driving range on user preference. For instance, at a remaining driving range of 5 km (equal to the trip length), the average likelihood of choosing an EMSS is below 30%. However, this likelihood increases dramatically to over 80% when the remaining driving range reaches 14 km. This underscores the importance of addressing battery insufficiency, as it can lead users to opt out of using an available e-moped. It also emphasizes the need for effective recharging strategies or mitigation measures. In addition to this, Fig. 5 clearly illustrates the modeled heterogeneity in user preferences for the remaining driving range. For example, at a remaining driving range of 10 km (double the trip distance), the likelihood of choosing an e-moped varies significantly among individuals, ranging from below 30% in the lower quantile to above 90% in the upper quantile. This variation underscores the importance of considering user heterogeneity in vehicle choice. Although we aim to represent current market conditions, it is important to note that the absolute values of these likelihoods are highly dependent on the values of other vehicle attributes. Therefore, in the following sections, we will explore how varying these additional vehicle attributes influences the likelihood of choosing EMSS.

6.2.2. Influence of varying vehicle attributes on the likelihood of choosing EMSS

In this analysis, we examine the percentage change in the likelihood of users choosing an EMSS under varying combinations of three key vehicle attributes: remaining driving range, walking time to the vehicle, and per-minute ride fee. The other two attributes are held constant, with an unlock fee of €1 and the slower vehicle type selected. The results are illustrated in Fig. 6.

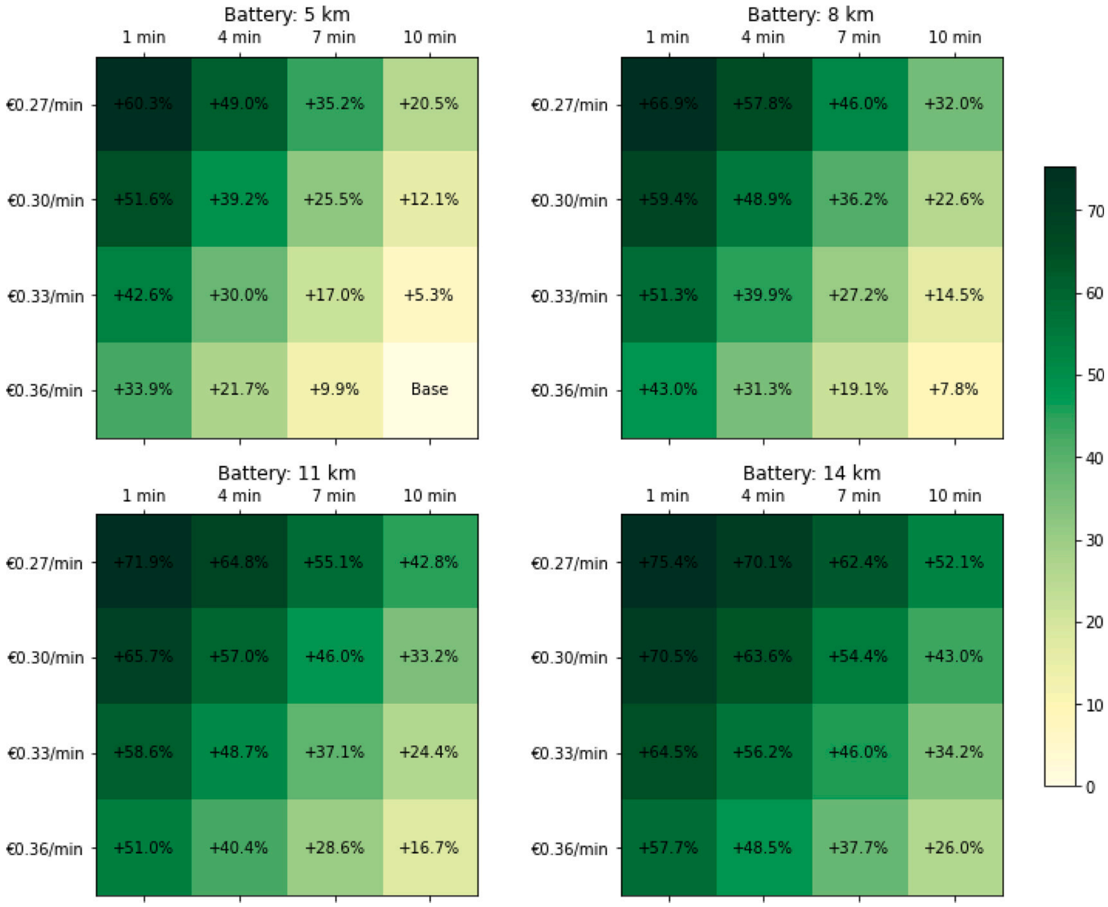


Fig. 6. Percentage change (from the base scenario) in the likelihood of choosing EMSS.

Fig. 6 illustrates the impact of walking distance and ride fee on the likelihood of selecting an e-moped, with variations across different battery levels. The baseline likelihood represents the least favorable combination of attributes, which includes the highest walking distance, the highest ride fee, and the lowest remaining driving range. Using this baseline as a reference, the changes in likelihood values were estimated for different attribute levels.

Notably, the figure underscores the crucial role of vehicle battery management strategies, showing that user choices are influenced by factors beyond walking distance and per-minute ride fee. For instance, when the walking distance is fixed at 4 min, an e-moped with only 5 km of remaining driving range requires a lower ride fee (€0.27/min) to achieve a higher likelihood of selection. However, if the remaining driving range falls within the comfortable range (e.g., 14 km), even the highest ride fee considered (€0.36/min) leads to a similar likelihood of selection. This indicates that users exhibit greater price sensitivity when battery levels are low, reinforcing the importance of maintaining sufficient battery levels to optimize e-moped adoption and the system's efficiency.

A similar analysis was conducted utilizing the unlock fee as the price component fixing the ride fee to its current market price of €0.33/min. The full Figure of the four heat-maps can be found in Appendix B. This scenario analysis reinforces that operators can mitigate the disutility of certain vehicle attributes by adjusting per-minute ride fees or unlock fees. However, pricing strategies have limitations. While they can help balance user preferences and optimize fleet utilization, remaining driving range remains a key determinant in user decisions, highlighting its crucial role in EMSS adoption.

7. Discussion and managerial insights

This section highlights key insights derived from our research, focusing on practical strategies for EMSS operators to enhance service efficiency and user satisfaction. The implications are based on the analysis of WTP indicators and the scenario analysis. Providing actionable recommendations for real-world applications. Further, the limitations of this research and potential directions for further research are discussed.

7.1. User-based relocation strategies through WTP and elasticity insights

Our findings suggest that even small price adjustments can significantly impact user behavior, particularly with respect to walking distance to access a vehicle. For example, reducing the ride fee by an average of €0.015 per minute can incentivize users to walk an additional minute to reach a vehicle. Similarly, a €0.24 reduction in the unlock fee has a comparable effect. Considering the approximate ride time from the provided context, the total reduction for the ride fee amounts to €0.225. This highlights the similar influence on user preference of both pricing strategies. Therefore, our research further suggests that both ride fees and unlock fees are effective tools for operators to manage vehicle distribution and encourage users to access vehicles that are farther away. The needed price reductions derived from our study are even smaller than those reported by Hoobroeckx et al. (2023), further highlighting the potential effectiveness of user-based relocation strategies. By strategically lowering fees for vehicles placed in lower-demand areas, operators can balance vehicle availability across their service area, enhancing overall system efficiency. Furthermore, the elasticity analysis indicates that all else being equal, a reduction in ride fees leads to the greatest increase in the likelihood of choosing EMSS, followed by a reduction in unlock fees and walking distance. This finding suggests that to maximize the market penetration of EMSS, operators should explore strategies that enable them to lower ride fees for consumers, while maintaining a balance with the company's financial viability.

7.2. Managing fleet utilization based on remaining driving range

While the analysis reveals that the latent variable on perceived range anxiety does not have a significant influence on user preference, the remaining driving range as a vehicle attribute has a substantial influence with lower ranges making vehicles less attractive. This highlights the importance of effective battery management strategies, as user choices are shaped by more than just walking distance and per-minute ride fees. Notably, users exhibit greater price sensitivity when battery levels are low, emphasizing the need for operators to maintain sufficient battery levels to optimize e-moped adoption and overall system efficiency.

Additionally, to mitigate the effect of lower remaining driving range, operators can incentivize users to utilize these e-mopeds. This strategy not only maximizes the use of the entire fleet but also helps prevent vehicles from becoming stranded or underutilized due to low battery levels. However, it is important to note the significant heterogeneity in user preferences with respect to the remaining driving range. Less experienced users may require higher incentives to choose vehicles with lower battery levels. By offering customized incentives based on user experience and vehicle range, operators can better manage their fleets and ensure a more balanced distribution of vehicles across different battery levels. Additionally, rather than solely relying on price incentives to manage fleet utilization, EMSS operators can also reduce range anxiety by providing enhanced information and user education. To effectively minimize uncertainties and improve user confidence, operators can implement several actionable measures:

Enhanced Information Systems in the App: EMSS operators can develop advanced interface features in the user app that provide detailed information about each vehicle's range. This could include visualizing how far the remaining driving range could potentially take the user (using a range circle) or allowing users to input their destination to check if the remaining driving range is sufficient for the trip.

User Education and Training: Educational content can be created within the app to guide users on maximizing battery efficiency, understanding the reliability of remaining driving range estimates, and knowing what to do if the battery runs out. This can help users feel more confident and informed when choosing vehicles with lower remaining driving ranges.

Interface Features on Vehicles: User-interface features can be incorporated directly into the vehicles that provide detailed information about the remaining driving range and whether the destination is reachable. This could involve displaying the remaining driving range in kilometers rather than just showing the state of charge as a percentage, offering detailed analytics on the expected range under different driving conditions, or integrating a navigation system that compares the available range with the trip length, as present in modern BEVs.

Lastly, while incentivizing users and mitigating range anxiety can optimize fleet utilization and improve operational effectiveness. Effective fleet management in terms of monitoring and balancing the remaining driving range of vehicles is crucial to ensure service reliability and user satisfaction.

7.3. Adapting to regulatory changes in vehicle preferences

In addition to the multiple factors that may influence vehicle preferences, our study points out the potential impact of regulatory changes. With the introduction of mandatory helmet regulations that standardize safety measures across different vehicle types, there has been a noticeable shift in user preference towards faster vehicles. This presents an opportunity for operators to adjust their pricing strategies accordingly. Based on WTP indicators, it may be feasible to increase the fees for faster vehicles by between €0.022 and €0.083 per minute or by €0.72 in the unlock fee without significantly deterring users. Operators should consider leveraging these insights to maximize revenue while maintaining high user satisfaction. By aligning pricing with user preferences for faster vehicles, they can better cater to market demand while ensuring compliance with safety regulations. Another strategic focus could be on providing more 45 km/h vehicles, especially in scenarios where competitive pricing should be maintained.

7.4. Limitations and future research

This study underlies certain limitations. First, the limited sample size may limit the generalization capabilities of the findings to the broader Dutch population, as discussed in Section 5.1. Future research should cover an extensive and diverse sample, including non-users and respondents from varied geographical regions, to further validate our findings. Second, our study is based on SP experiments for a fixed context to simulate critical range situations. The hypothetical choices may not fully reflect actual behavior and may not capture the full variability of real-world conditions, including factors such as weather, trip purposes, and distances (Hoobroeckx et al., 2023). Future research should incorporate revealed preference (RP) data to address the hypothetical bias inherent to SP data and validate the findings. Lastly, advanced modeling techniques like latent class models could better capture user heterogeneity and the influence of latent variables.

8. Conclusion

This study explores the key determinants of vehicle choice in electric moped sharing systems (EMSS), focusing on both user-specific and vehicle-specific factors. It is among the first to investigate how range anxiety influences user preferences in critical range situations, considering both the remaining driving range and attitudinal factors such as perceived range anxiety. Additionally, the research assesses the effects of new pricing strategies, like unlock fees, and regulatory changes, such as mandatory helmet laws. Using a stated preference experiment and a Hybrid Choice Model (HCM), we quantified these effects to gain a deeper understanding of user behavior.

The findings reveal that users have a clear preference for lower fees, shorter walking distances, and vehicles with higher remaining driving ranges. There is substantial heterogeneity in user preferences, particularly concerning per-minute ride fees and remaining driving range, indicating that these factors influence user decisions differently across individuals. Some users are even willing to walk longer distances to access vehicles with more favorable attributes. The introduction of mandatory helmet regulations may have shifted preferences towards faster vehicles, demonstrating that regulatory interventions can substantially alter user behavior and competitive dynamics within EMSS. Scenario analysis further illustrates how varying vehicle attributes and pricing strategies affect market share and fleet utilization. Incentivization through dynamic pricing, based on vehicle location and remaining driving range, emerges as a powerful tool for improving service availability and user satisfaction. These insights are valuable for EMSS operators, enabling them to tailor strategies that balance cost, convenience, and service availability, thereby optimizing fleet utilization and enhancing user adoption in different contexts.

CRediT authorship contribution statement

Sören Paul Burghardt: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Sara Momen:** Writing – review & editing, Supervision, Conceptualization. **Yousef Maknoon:** Writing – review & editing, Supervision. **Shadi Sharif Azadeh:** Writing – review & editing, Supervision, Resources, Conceptualization. **Kuldeep Kavta:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used generative AI tools in order to enhance readability and ensure correct grammar and spelling. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix A. Full set of parameter estimates for the HCM model

See Tables A.5–A.7.

Table A.5
Model Fit indicators HCM.

Metric	Value
Number of inter-individual draws	5000 (Halton)
LL(start)	−2421.42
LL(whole model) at equal shares, LL(0)	−2082.85
LL(whole model) at observed shares, LL(C)	−1711.64
LL(final, whole model)	−1388.24
Rho-squared vs equal shares	0.3335
Adj. Rho-squared vs equal shares	0.3042
Rho-squared vs observed shares	0.1889
Adj. Rho-squared vs observed shares	0.1708
AIC	2898.47
BIC	3074.78
Estimated parameters	52

Table A.6
Parameter estimates for the HCM model.

Parameter	Estimate	s.e.	t.rat.(0)	p-value)
ASC_{MSS}	10.514	1.786	5.8862	0.000
$b_{UnlockFee}$	−1.419	0.223	−6.343	0.000
$b_{VehicleType}$	−1.023	0.212	−4.830	0.000
$b_{Distance}$	−0.342	0.043	−7.969	0.000
$b_{RideFee}$	−25.47 (8.948)	0.127	–	–
$b_{Battery}$	0.282 (0.079)	0.001	–	–
$b_{previous}$	−1.719	0.629	−2.731	0.005
b_{bike}	−2.212	1.107	−1.996	0.022
b_{alone}	1.212	0.461	2.628	0.005
b_{shared}	−0.864	0.441	−1.959	0.052
b_{low_income}	−1.18	0.471	−2.511	0.005

Table A.7
Latent variable parameter estimates (Attitude towards EMSS) HCM.

Parameter	Estimate	s.e.	t-rat.(0)	p-value)
$\eta\_emop(LV1)$	0.830	0.304	2.723	0.003
$\gamma\_LV1 - previous$	0.829	0.217	3.810	0.000
$\gamma\_LV1 - nationalityDutch$	−0.340	0.166	−2.04	0.043
$\gamma\_LV1 - educationBachelor$	0.370	0.163	2.271	0.024
$\gamma\_LV1 - educationMaster$	−0.315	0.142	−2.223	0.027
ζ_{emop_1}	3.49265	1.07007	3.2639	0.0014
$\tau_{\text{emop}_1^1}$	−8.66344	2.42223	−3.5766	0.0005
$\tau_{\text{emop}_1^2}$	−5.17326	1.42389	−3.6332	0.0004
$\tau_{\text{emop}_1^3}$	−3.04480	0.99303	−3.0662	0.0026
$\tau_{\text{emop}_1^4}$	4.25646	1.18729	3.5850	0.0005
ζ_{emop_2}	2.5045	0.5288	4.7359	0.0000
$\tau_{\text{emop}_2^1}$	−6.0139	1.1475	−5.2408	0.0000
$\tau_{\text{emop}_2^2}$	−4.3075	0.7932	−5.4271	0.0000
$\tau_{\text{emop}_2^3}$	−2.1280	0.5536	−3.8439	0.0002
$\tau_{\text{emop}_2^4}$	3.3105	0.7359	4.4984	0.0000
ζ_{emop_3}	1.0114	0.2103	4.8081	0.0000
$\tau_{\text{emop}_3^1}$	−2.8589	0.4039	−7.0784	0.0000
$\tau_{\text{emop}_3^2}$	−1.2435	0.2692	−4.6191	0.0000
$\tau_{\text{emop}_3^3}$	−0.2465	0.2456	−1.0038	0.3173
$\tau_{\text{emop}_3^4}$	1.8748	0.3177	5.9007	0.0000
ζ_{emop_4}	1.1071	0.2301	4.8111	0.0000
$\tau_{\text{emop}_4^1}$	−5.2700	1.0343	−5.0950	0.0000
$\tau_{\text{emop}_4^2}$	−3.0549	0.4339	−7.0395	0.0000
$\tau_{\text{emop}_4^3}$	−0.6956	0.2661	−2.6137	0.0100
$\tau_{\text{emop}_4^4}$	2.3241	0.3639	6.3597	0.0000

Appendix B. Scenario analysis unlock fee

In this analysis, we set the per-minute ride fee to a fixed value of €0.33/min and evaluated how variations in the unlock fee impact the likelihood of choosing an e-moped. The base likelihood corresponds to the least favorable attribute combination (see Fig. B.7).

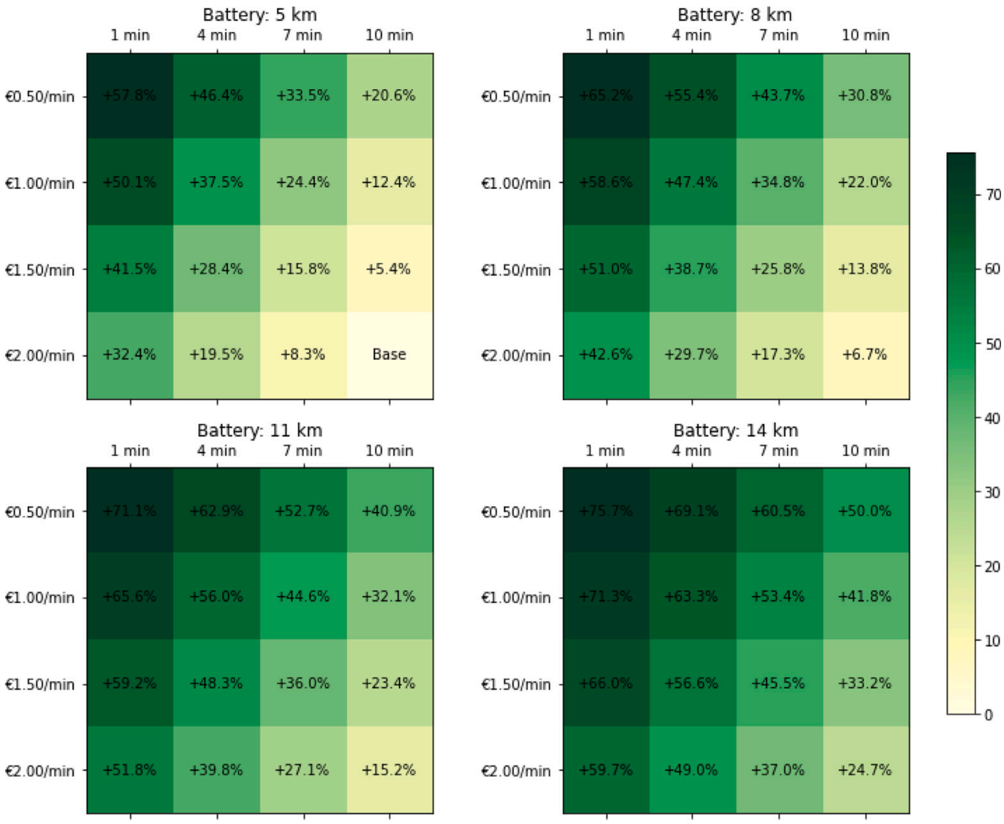


Fig. B.7. Likelihood of choosing EMSS based on varying remaining driving range, walking time, and unlock fee levels.

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