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DOI
10.1016/j.rtbm.2023.101021

Publication date
2023

Document Version
Final published version

Published in
Research in Transportation Business and Management

Research in Transportation Business & Management 50 (2023) 101021

Contents lists available at ScienceDirect

Research in Transportation Business & Management

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

Travel choices in (e-)moped sharing systems: Estimating explanatory variables and the value of ride fee savings

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ARTICLE INFO

Keywords:
Shared moped
Micromobility
Pricing
Travel behaviour
Stated preferences

ABSTRACT

Free-floating (e-)moped sharing systems are becoming increasingly popular and provide new ways of travel in urban areas. The vehicles offer the flexibility of one-way transportation, though the downside for service providers of free-floating shared fleet systems is that their operations may result in a spatial-temporal imbalance of the vehicle distribution within the system. The potential effectiveness of user-based relocation strategies depend on the trade-offs users make between (reduced) ride fees and (prolonged) walking times. It is therefore essential to establish the trade-offs exercised by users in the context of moped sharing systems. We elicit travel preferences and assess how vehicle choice is influenced by user characteristics, travel context and alternative-specific attributes by means of a choice experiment. Our findings indicate that respondents in the Netherlands require a reduction of €0.02 of the ride fee for each additional walking minute required for accessing a vehicle. The application of our model demonstrates that vehicle availability, pricing, trip characteristics, and socioeconomic factors significantly drive adoption rates, emphasising the importance of understanding user preferences and thereby the factors shaping the acceptance and utilisation of e-moped sharing services. These findings offer essential implications for policymakers and operators, enabling them to tailor e-moped sharing services to diverse user segments as well as understanding the impact of policies, such as helmet mandates. The outcomes presented in this paper are likely to be applicable to other vehicle sharing systems with comparable design and management configurations.

1. Introduction

The first-ever vehicle sharing system dates back to 1948 when a car-sharing cooperative was introduced in Zurich, Switzerland. This sharing platform allowed members that were economically unable to purchase their own car to share a car among a group (Ataç, Obrenović, & Bierlaire, 2021; Shaheen, Sperling, & Wagner, 1998). In the last couple of decades a plethora of shared mobility services have been introduced. Advantages mentioned include supporting cities in coping with the growing pressure on urban passenger transport systems, to make more efficient use of scarce urban space, and to reduce emissions within urban areas (Kamargianni, Li, Matyas, & Schäfer, 2016; Lazarus, Pourquier, Feng, Hammel, & Shaheen, 2020). Technological innovations have paved the way to making these systems more easily accessible to users and thereby contributing to their scalability.

Vehicle sharing systems should be distinguished from ride-sharing and ride-hailing systems. Ride-sharing and ride-hailing systems imply interaction with another user, mainly the (private) owner or driver of the vehicle (e.g. Uber). This is different from vehicle sharing, where the user is provided with short-term and occasional access to a vehicle that is owned by private companies, governments or non-profit organisations. Nowadays, many cities worldwide offer some form of shared (micro)mobility. Popular modes in vehicle sharing systems nowadays are either station-based or free-floating (electric) cars, bicycles, kick-scooters, and e-mopeds (Glöss et al., 2020; Heineke, Kloss, Scurtu, & Weig, 2019; McKenzie, 2020), with the bicycle being the most popular (Lazarus et al., 2020; McKenzie, 2020; Ploeger & Oldenziel, 2020; Roukouni & Correia, 2020; Wilkesmann, Ton, Schakenbos, & Cats, 2023). Except for cars, the other modes are also referred to as micromobility because one typical characteristic is their low weight (Gioldasis

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https://doi.org/10.1016/j.rtbm.2023.101021
Received 9 August 2022; Received in revised form 21 July 2023; Accepted 27 July 2023
Available online 5 August 2023

& Christoforou, 2021). The introduction of these services has enlarged the mobility options and flexibility for last-mile transport connecting to public transport (Degele et al., 2018; Gimon, 2021; Glöss et al., 2020).

Micromobility services predominantly operate in a predefined service area, primarily in urban areas, which allows the modes to be free-floating or dock-less. These free-floating vehicle sharing systems offer the user the flexibility of one-way transportation without the need to return the vehicle to a specific location within the service area. The downside of this flexibility is that it is likely to lead to a spatial-temporal imbalance of the system caused by asymmetric demand patterns (Arias-Molinares, Romanillos, García-Palomares, & Gutiérrez, 2021; Ataç et al., 2021; Gimon, 2021). This can result in high vehicle idle times of vehicles that are left in lower demand areas due to oversupply. Worse still, it may lead to an under-supplied demand in higher demand areas. One strategy that can be applied to reduce this imbalance is adopting a supply-side management strategy, namely operator-based relocation. This can become financially prohibitive due to the costs of related logistics and staff deployment. Alternatively, user-based relocation, a demand-management strategy, may address vehicle imbalance by offering users (monetary) incentives to stimulate them to relocate vehicles within the system by means of nudging them to pick-up (drop-off) a vehicle that is located further away than their desired start (end) location (Angelopoulos, Gavalas, Konstantopoulos, Kypriadis, & Pantziou, 2018; Neijmeijer, Schulte, Tierney, Polinder, & Negenborn, 2020; Pfrommer, Warrington, Schildbach, & Morari, 2014; Singla et al., 2015). The potential effectiveness of user-based relocation strategies depend on the trade-offs users make between (reduced) ride fees and (prolonged) walking times. It is therefore paramount for shared fleet providers to identify the value of ride fee savings.

Studies by Pfrommer et al. (2014), Wu (2019) and Neijmeijer et al. (2020) acknowledge the relevance of (dynamic) pricing strategies in the context of bicycle sharing, car sharing, and (e-)moped sharing, respectively. Pfrommer et al. (2014) stated that future research should focus on the behavioural aspect concerning users' acceptance and participation in relocation strategies and the required level of incentives provided to stimulate this participation. Wu (2019) asserted that the interaction between user behaviour and system design needs to be further investigated and especially lacks in relation to shared fleets. The author also mentions that most studies are based on synthetic user behaviour rather than empirical evidence concerning user behaviour. Neijmeijer et al. (2020) was the first to conduct a case study applying a dynamic pricing strategy in a free-floating e-moped sharing system (MSS). They concluded that even small price deviations could be effective in stimulating changes in travel patterns. The results were limited to aggregate system performance metrics, neglecting individual behaviour aspects.

It is insofar unknown what are the determinants related to individual vehicle choice in moped sharing systems and in particular the underlying trade-off between ride fee and walking time which is essential for the design of user-based relocation pricing schemes. We address this knowledge gap by empirically underpinning users' response to such a pricing scheme by means of a choice experiment. In particular, we study the context of a free-floating MSS operating in the Netherlands by means of distributing a survey among its users.

The remainder of this paper is organised as follows. In the next section we describe the experiment and survey design, data collection, and choice analysis methodology. Next, we present and discuss the results. Subsequently, we elucidate the implications of our model by means of a scenario analysis. Lastly, we conclude with a discussion of study implications and limitations, as well as outlining directions for further research.

2. Methodology

We designed and conducted a stated choice experiment that was distributed among MSS users to determinants of their vehicle choice. The experiment was included in a survey that also collected personal characteristics. In the following, we present the context and key characteristics of the MSS in question, the choice experiment, the choice model which is applied to analyse the survey data and provide information on the data collection performed.

2.1. Moped sharing system context and characteristics

The shared mobility landscape in the Netherlands includes in addition to moped sharing also car sharing, bike sharing, ride sharing and on-demand services. A recent analysis by the Netherlands Institute for Transport Policy Analysis Jorritsma, Witte, Alonso-Gonzáles, and Hamersma (2021) concluded that 2–6% of the Dutch population make use of car sharing services and 10% make use of a bike-sharing scheme, with higher shares observed in urban regions. Unfortunately, the analysis did not cover shared mopeds.

There are several MSS operators currently active in the Netherlands, namely, felyx, Check and Go Sharing. Our survey was conducted among registered users of felyx services. During the period when the survey was conducted (July 2021), felyx operated shared moped services in various cities across the Netherlands, Belgium, and Germany. In particular, felyx mopeds were available for use in eight urban areas in the Netherlands. These areas included the three largest metropolitan regions of Amsterdam, Rotterdam, and The Hague, as well as five medium-sized cities, namely (Delft, Eindhoven, 's Hertogenbosch, Groningen, and Haarlem).

In the following we present some key characteristics of the MSS in question to underpin some of the choices we made in the design of the survey. An empirical analysis of data made available by the service operator reveals that the travel distances are distributed with an average of approximately 4 km and the vast majority (80%) of the trips varying between 1 and 7 km (see Fig. 1).

Next, we investigate the empirical distribution of users' distance to the closest vehicle upon opening the app. As can be seen in Fig. 2, distances are typically in the low hundreds of meters. Assuming a walking speed of 1.4 m/s, we expect majority of walking times to range between 4 and 7 min.

As for ride fees, those were constant in all cities where the shared moped services operated at the time of the survey, except for Eindhoven and Rotterdam. At the time data was collected, the regular and reduced prices were set to 0.24 and 0.30 Euros per minute, respectively.

2.2. Stated choice experiment

Respondents were provided with a survey that included a choice experiment consisting of twelve choice situations. The choice situation displayed a choice between two (unlabelled) MSS alternatives for making a trip between an origin and a destination, followed by a choice between the chosen alternative and an opt-out alternative. Several opt-out alternatives are included with the aim to broaden the choice options to better imitate real-life choice situations for the respondent, see Fig. 3. The modes that are included are assumed to be available in the same urban environment where MSS operators provide their services. No information is provided on any attribute related to the opt-out options, keeping the main focus of the choice experiment on assessing vehicle choice between two MSS alternatives.

The MSS alternatives were described using four attributes; ride fee (€/minute), walking time (minutes), vehicle type, and vehicle location. The choice situation was enriched with trip characteristics by describing a context profile. The context variables that were included are trip purpose, trip start location, precipitation, and trip distance (kilometres).

We varied the ride fee attribute over four levels; 0.18, 0.24, 0.30, and 0.36 €/minute. The two middle levels correspond to the regular and reduced fee levels used by the operator during the data collection period. Also, four levels for walking time were included; 1, 4, 7, and 10 min. We specify this set of values to assess the impacts of walking times which are either shorter or longer than those typically experienced, yet are within empirical range of observed values (Fig. 2). This provides

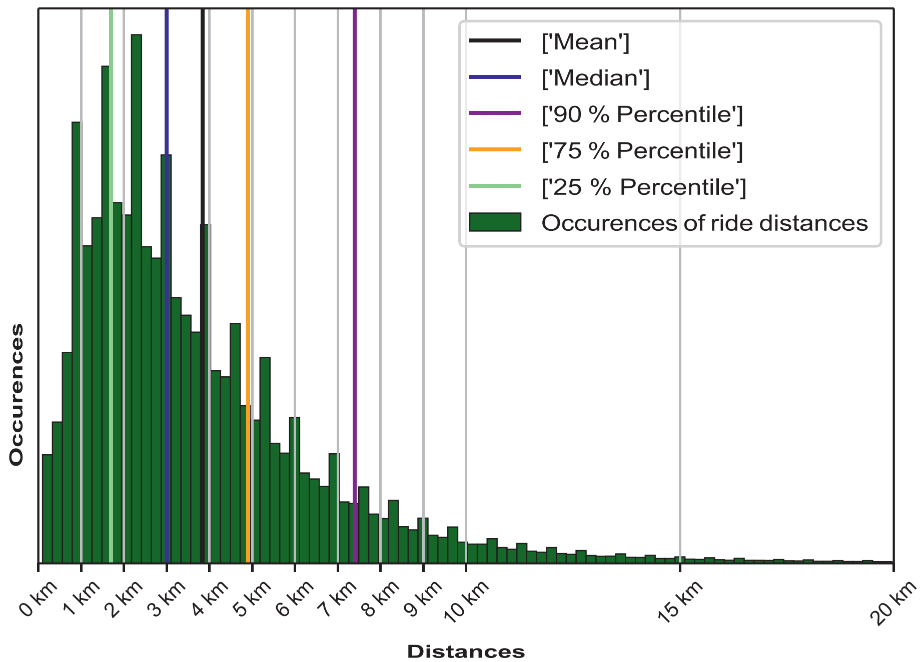

Fig. 1. Distribution of ride distance.

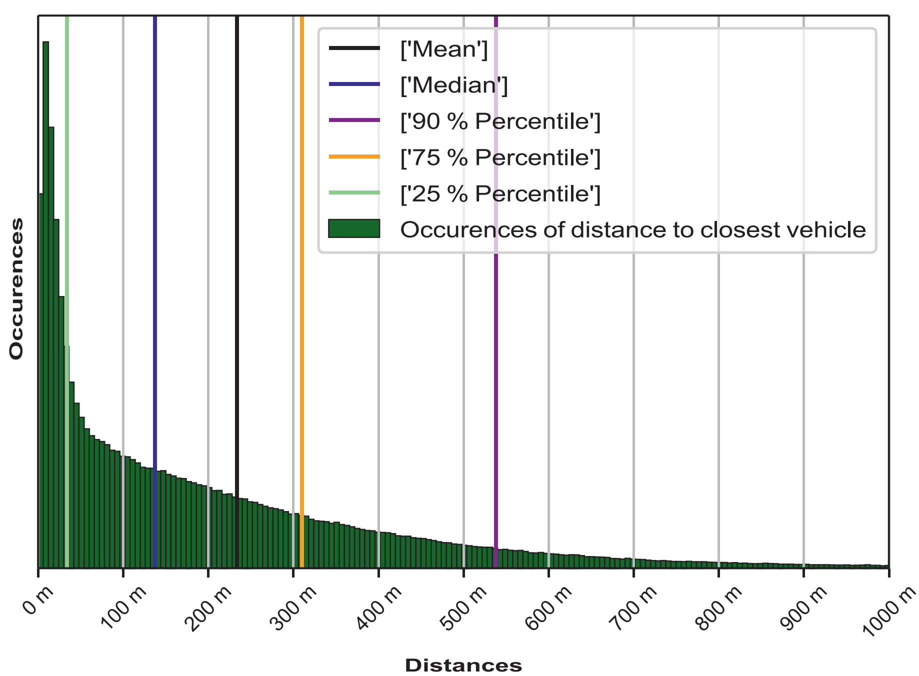

Fig. 2. Distribution of distance to the closest vehicle.

insights into the trade-offs associated with other relevant attributes, such as price.

Vehicle type is a dummy attribute that was varied over two levels indicating the speed and helmet obligation: 30 km/h + no helmet, and 45 km/h + helmet.[2] The vehicle location indicated a vehicle either being en-route or off-route in relation to the trip destination. We used Ngene to create a D-efficient design for the alternative attributes so as to create four blocks of three choice profiles each (twelve in total). We used small priors to indicate the expected direction for each parameter. The main reason we used a D-efficient design is that it prevented the occurrence of dominant alternatives in the choice profiles.

The context variables trip purpose, trip start location, and precipitation were all varied using two levels. Trip purpose distinguished between leisure and commuting trips. The trip start location indicated either starting the trip from home or not from home (i.e. home-based versus activity-based trips). The precipitation attribute specified the weather conditions as either dry or rainy. The trip distance was varied over four levels; 1, 3, 5, and 7 km. The context variables and levels were varied with an orthogonal fractional factorial experimental design. We created eight context profiles divided over two blocks. We varied the

[2] This study was conducted before the general helmet obligation for both moped types was announced (commenced on January 1, 2023).

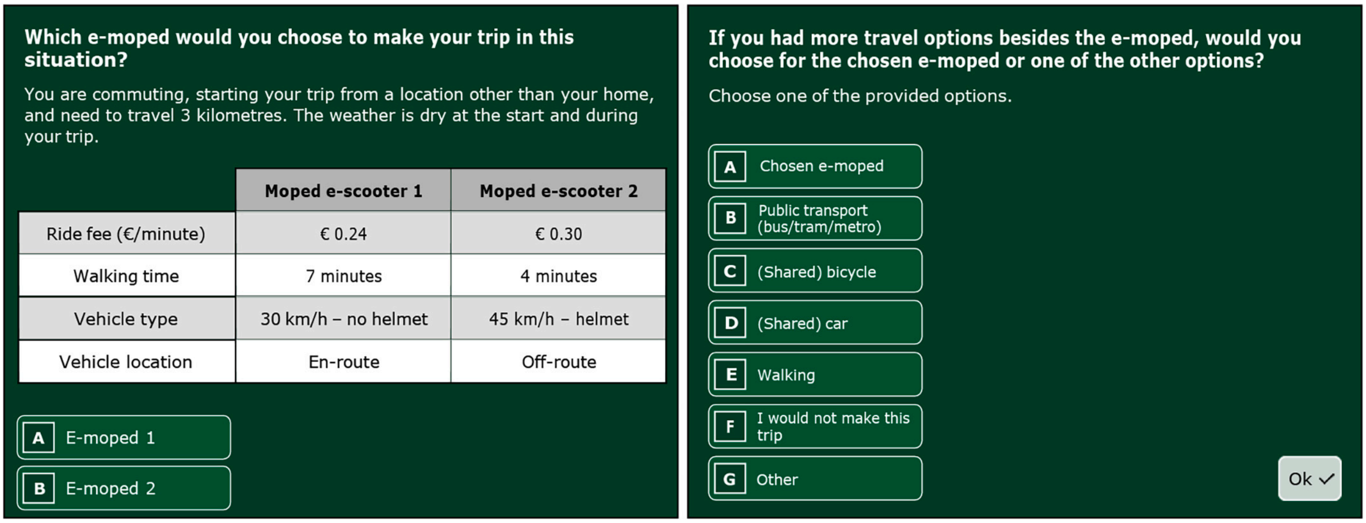

Fig. 3. Stated choice experiment choice situation example (translated from Dutch).

context to test for the impacts of various trip characteristics. This way we aim to investigate the influence of the characteristics on MSS choice and MSS choice and opting out.

Eventually, we nested the choice profiles under the context profiles, creating 96 unique choice sets. These choice sets were divided over eight versions containing twelve choice situations each. Respondents encountered three choice situations per context situation (i.e. context varied four times). An example of a choice situation is presented in Fig. 3. Each respondent first makes a choice between two MSS alternatives, followed by a choice between the chosen MSS alternative and opting out.

In addition, nine questions were included in the survey to collect personal characteristics from respondents. First, we asked respondents about the frequency of their MSS usage (number of times per week) and which operators they were familiar with. Second, respondents were asked to indicate their gender, year of birth (age), highest education level, income level, employment status, and household characteristics. We also asked respondents which vehicles they own (e.g. a car or bicycle).

2.3. Data collection

The survey was sent out to registered users of felyx, one of several MSS operators currently active in the Netherlands as described above. Data collection took place between 19 July 2021 and 26 July 2021. Users were selected based on the criterion that they had made at least one trip in the past 30 days. The survey was distributed online via email to 6000 customers that were registered in Rotterdam, Haarlem, Eindhoven, and The Hague. This sample of invited users was selected randomly from the population of registered users which amounted to almost 800,000 people at the time data was collected.

Respondents were randomly assigned to one out of the eight survey versions. The total number of respondents that started the survey was 568. The number of respondents that completed the entire survey is 414 (completion rate 73%, response rate 6.9%). The total number of observations that were collected is 4968.

A comparison of the age statistics of the sample with those of the registered user population shows a very good correspondence with the median age of the sample being 30 years compared to 29 years in the relevant population. Respondents are somewhat over-represented in our sample compared to their share in the relevant users population – with 36% vs. 29%, respectively.

2.4. Choice model estimation

The collected stated choice data was used to estimate a series of choice models using the random utility maximisation theoretical framework. Random utility maximisation assumes that the decision maker aims to maximise utility when choosing between alternatives and chooses for the alternative with the highest perceived utility. We used a linear-additive utility maximisation decision rule which is expressed by the following formula (Train, 2009):

$$U_{in} = V_i + \varepsilon_{in} = \sum_m \beta_m \cdot x_{im} + \varepsilon_{in} \tag{1}$$

Where:
U_{in} is the total utility associated with alternative i by individual n
V_i is the systematic utility of alternative i
ε_{in} is the unobserved utility associated with alternative i by individual n
β_m is a taste parameter associated with attribute m
x_{im} is the attribute value of attribute m of alternative i

The total utility U_{in} associated with alternative i is denoted by the summation of the systematic utility and the error component. The systemic utility expresses the utility that can be related to observed factors. The error component ε_{in} captures the utility of unobserved factors, heterogeneity in tastes and randomness in choices (Train, 2009).

The Multinomial Logit (MNL) model is the most frequently applied discrete choice model. One of the main assumptions of the MNL model is that ε is i.i.d. for all alternatives, i.e. the unobserved factors are uncorrelated over alternatives and have the same variance for all alternatives. This restrictive assumption provides a convenient and therefore prevalent form for the choice probability (Train, 2009). Eq. 2 provides the logit choice probability formula retrieved from Train (2009) and Ortúzar and Willumsen (2011):

$$P_{in} = \frac{e^{V_{in}}}{\sum_j e^{V_{jn}}} \tag{2}$$

Where:
P_{in} is the choice probability of alternative i by individual n
$\sum_j$ is the summation over utility of all alternatives included in the choice set of individual n

The context attributes that were included in the experiment describe the background of the choice situation, creating more realistic choice situations, and allow for estimation of the effect of context on decision-making. To express the effect of context on U_{in}, the context attributes are included as main effects. Thereby, we test for effects between alternative attributes and context variables as described in Oppewal and Timmermans (1991). We also examined whether there were non-linear effects of the ratio attributes and effects between the alternative attributes and context variables using likelihood ratio tests.

Finally, model estimation results allow to empirically establish the Value of Ride Fee Savings (VoRFS). It can be calculated by dividing the value of the coefficient for walking time by the value of the coefficient for ride fee. The value of which reflects how much of a reduction in the ride fee (€/minute) respondents expect for accepting one additional walking minute.

3. Choice model estimation results

Overall, respondents choose the two MSS options almost equally often (51% vs 49%). Additionally, the choice distribution between the chosen e-moped and the opt-out option in the secondary question is 28.4% for the MSS and 71.6% for opting out for another travel option. Based on a comparison of the opt-out percentage in the sample and reservation data acquired from the aforementioned MSS operator, we conclude that the opt-out rate reported in the experiment is relatively high. This can be arguably attributed to the context descriptions provided in the stated choice experiment. In reality customers might not even open the application to reserve a vehicle when it is raining or when planning their trip to work due to related mode choice preferences.

Multiple steps are required to arrive at our final choice model specification. We adopt an iterative backward model estimation procedure where significant (at the 95% confidence level) and meaningful coefficients are maintained in the model. Next, we check the effect of respondent characteristics and vehicle ownership factors. Table 1 provides an overview of the variables included in the final model, along with information on the type, the units, coding and levels of the attributes. We dummy coded the categorical MSS attributes, as these were dummy coded in the Ngene syntax. The other categorical variables were effects coded (the reference level is indicated by (ref.)). The final utility specification is given in Eq. 3. The final model has two identical utility functions for the MSS alternatives (V_{MSS}). The opt out utility ($V_{Opt\,out}$) is fixed to 0. The taste parameters (β) of the included variables are estimated using PandasBiogeme (Bierlaire, 2020).

$$\begin{aligned} V_{MSS} \quad &= ASC_{MSS} + \beta_{rf}{*}rf + \beta_{wt}{*}wt + \beta_{tp}{*}tp + \beta_{vl}{*}vl \\ &+\beta_{pp}{*}pp + \beta_{st}{*}st + \beta_{we}{*}we \\ &+\beta_{ds}{*}ds + \beta_{qds}{*}ds^2 \\ &+\beta_{ge}{*}ge \\ &+\beta_{il_1}{*}il_1 + \beta_{il_2}{*}il_2 + \beta_{il_3}{*}il_3 + \beta_{il_4}{*}il_4 + \beta_{il_5}{*}il_5 \\ &+\beta_{co}{*}co + \beta_{bo}{*}bo \\ V_{Optout} &= 0 \end{aligned} \tag{3}$$

Table 2 provides an overview of the estimated parameters and presents the model fit of the final model. The model contains eighteen parameters that are all significant at the 95% confidence level. All parameters have the expected signs. In the following, we discuss the interpretation of the included attributes.

The alternative-specific constant (ASC) for MSS, ASC_{MSS}, has a negative sign. The utility of the MSS is 0.550 lower compared to the provided opt-out alternatives, all else being the same. I.e. the value of ASC_{MSS} indicates the systematic utility difference between the MSS alternative and the grouped opt-out alternatives, when the MSS attribute values are equal to 0 and for an average context profile. Even though the context situations are balanced by design, the value of ASC_{MSS} might not be identical to the true value. In other words, the dis-preference towards MSS is arguably caused by the skewed distribution of the context situations compared to reality.

The parameter values β_{rf} and β_{wt} of the alternative attributes ride fee (rf) and walking time (wt) show an expected negative impact of increasing both values (−3.900 and − 0.082, respectively). As mentioned in Section 2.4, the VoRFS can be calculated by dividing the

Table 1
Name, symbol, type, units, coding, and description and levels of the included variables.

Name	Symbol	Type	Units	Coding	Description and levels
ASC MSS	ASC_{MSS}	–	–	–	–
Ride fee	β_{rf}	Numerical	€/minute	–	0.18, 0.24, 0.30, 0.36
Walking time	β_{wt}	Numerical	minutes	–	1, 4, 7, 10
Vehicle type	β_{tp}	Categorical	–	dummy	30 km/h (no helmet) (ref.), 45 km/h (helmet)
Vehicle location	β_{vl}	Categorical	–	dummy	En-route (ref.), off-route
Trip purpose	β_{pp}	Categorical	–	effects	Commuting (ref.), leisure
Trip start location	β_{st}	Categorical	–	effects	Not home (ref.), home
Precipitation	β_{we}	Categorical	–	effects	Dry (ref.), rain
Trip distance	β_{ds}	Numerical	kilometres	–	1, 3, 5, 7
Gender	β_{ge}	Categorical	–	effects	Female (ref.), not female
Income level	β_{il}	Categorical	€/month	effects	Less than €1000/month, 1000–2000 €/month, 2000–4000 €/month, 4000–10,000 €/month, more than 10,000 €/month, prefer not to say (ref.)
Car ownership	β_{co}	Categorical	–	effects	No car (ref.), car
Bicycle ownership	β_{bo}	Categorical	–	effects	No bicycle (ref.), bicycle

Table 2
Estimated parameters and model fit of the final model.

Name	Symbol	Value	Std err	*t*-test	*p*-value
ASC MSS	ASC_{MSS}	−0.550	0.205	−2.680	0.007
Ride fee	β_{rf}	−3.900	0.436	−8.950	0.000
Walking time	β_{wt}	−0.082	0.009	−9.140	0.000
Vehicle type	β_{tp}	−0.452	0.054	−8.390	0.000
Vehicle location	β_{vl}	−0.223	0.060	−3.750	0.000
Trip purpose	β_{pp}	0.104	0.032	3.210	0.001
Trip start location	β_{st}	0.175	0.032	5.440	0.000
Precipitation	β_{we}	−0.403	0.033	−12.300	0.000
Trip distance	β_{ds}	0.180	0.066	2.710	0.007
Trip distanceˆ2	β_{qds}	−0.016	0.008	−2.010	0.045
Gender	β_{ge}	0.222	0.036	6.240	0.000
Income level 1	β_{il_1}	0.422	0.113	3.730	0.000
Income level 2	β_{il_2}	0.470	0.099	4.740	0.000
Income level 3	β_{il_3}	0.389	0.090	4.350	0.000
Income level 4	β_{il_4}	0.217	0.105	2.070	0.038
Income level 5	β_{il_5}	−1.450	0.366	−3.980	0.000
Car ownership	β_{co}	0.226	0.038	5.920	0.000
Bicycle ownership	β_{bo}	−0.127	0.041	−3.070	0.002
# Parameters	18				
Initial LL	−5457.906				
Final LL	−3804.509				
ρ^2	0.303				
BIC	7762.212				

value of β_{wt} by the value of β_{rf}. The obtained VoRFS amounts to €0.02 of ride fee reduction for each additional walking minute. This value implies that respondents require a reduction of €0.20 per ride fee minute if they would need to walk to a vehicle that is ten minutes away from their departure location. This exemplifies that the expected financial compensation for a ten minute walking time is very high since this fee reduction corresponds to 67% of the standard ride fee (€0.30/min).

The dummy coded alternative attribute parameter β_{tp} for vehicle type (*tp*) shows that utility declines (−0.452) for the 45 km/h type compared to the 30 km/h type. One possible explanation for this difference is that people dislike having to wear a helmet. At the time data collection took place, the possibility of the helmet obligation law being extended in the Netherlands to include 30 km/h mopeds (Rijksoverheid, 2021) raised concerns about its potential negative influence on the adoption of MSS. Another reason could be that people dislike having to ride on the road (as opposed to bicycle lanes), which is mandatory in the Netherlands when riding a 45 km/h moped. The dummy coded attribute β_{vl} for vehicle location (*vl*) shows the expected negative (−0.223) impact of a vehicle being off-route (i.e. walking detour to access the vehicle) in relation to the travel destination.

As mentioned before, we also test for all interaction effects between the alternative attributes and the context variables. Only two of all possible interactions are found significant and the magnitude of those is found negligible. Moreover, they did not add value to the model interpretation. We therefore conclude that the effects found for each of the alternative attributes are independent from the context attributes. Correspondingly, in the remainder we only discuss the influence of the main effects.

The context variables for trip purpose (*pp*), trip start location (*st*) and precipitation (*we*) are effects coded. The parameter β_{pp} for trip purpose indicates a greater preference towards MSS when used for leisure rather than for commuting. This is in line with the MSS adoption results mentioned by Aguilera-García, Gomez, Sobrino, and Díaz (2021) who stated that MSS tend to be primarily used for leisure trips. The parameter of the second context variable trip start location suggests that trips starting at a location other than home are more likely, all other things being equal, to use MSS, than trips originating at home. This is in line with expectations since travellers are more familiar with public transport options available in their vicinity and can be more easily performed by vehicles owned by the user when departing from their home location. Finally, as can be expected, the value of the parameter β_{we} (−0.403) for the precipitation variable reflects the negative impact of rainy weather conditions on the propensity to use MSS. The utility drop can be explained by the characteristics of the vehicle, which does not provide cover against rain. To conclude, the context variables showed that respondents have a preference for using MSS compared to the opt-out options for leisure trips, not starting at home (activity-based trips), and during dry weather.

We study the impact of trip distance (*ds*) on the preference for choosing MSS by specifying two parameters, β_{ds} and β_{qds} (parameter of the quadratic component for trip distance), see Eq. 3. The former is found positive whereas the latter is negative. Their joint effect means that the contribution to utility of an increasing distance peaks at five kilometres and then starts to drop. This effect is expected when comparing the known (empirical) distribution of trip length of reservations, where 75% of all trips are between zero and five kilometres. The non-linear utility contribution function for trip distance is plotted in Fig. 4.

Next, we turn to investigating the role of respondent characteristics. The value of β_{ge}, the parameter for gender (*ge*), shows that, all else being the same, males perceive MSS more favourably than females. This preference is plausible as it can be explained by inspecting acquired data on gender distribution of the MSS operator user population, which clearly showed a skewed distribution towards males. This observation is in line with findings from e.g. Aguilera-García, Gomez, and Sobrino (2020) and Degele et al. (2018). In all of the model specifications that we tested for, respondents' age is found to be insignificant in explaining their choices. A total of five parameters are estimated for the effects coded income level (*il*) attribute. β_{il_1} up to β_{il_4} all show a preference for using MSS compared to β_{il_5} and "prefer not to say", with the third and fourth income group showing a reduction in the parameter value compared to the first two income groups. This reveals that the last two groups, group five (−1.450), i.e. highest income range, and six, i.e. "prefer not to say", both show a lower preference towards MSS. The finding in relation to the impact of income resonates with Aguilera-García et al. (2020) who imply that this group prefers to use their private vehicles instead.

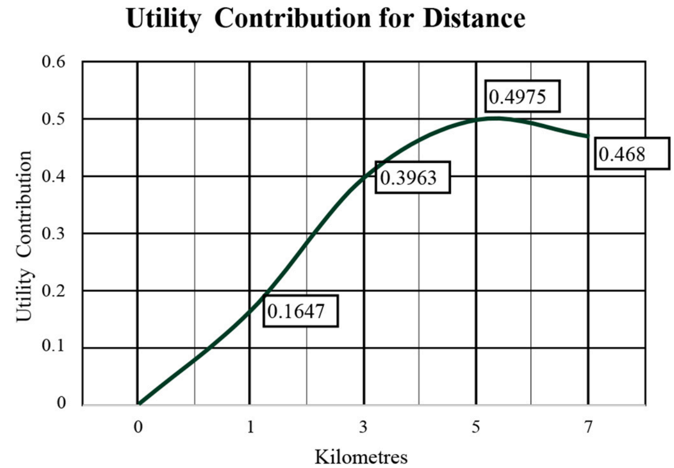

Fig. 4. Non-linear effect of travel distance due to quadratic component.

Finally, when a respondent owns a bicycle (*bo*) then the average utility of the MSS alternative decreases ($\beta_{bo} = -0.127$). In contrast, owning a car (*co*) increases the average utility of MSS ($\beta_{co} = 0.226$). Given the relatively short distances considered in our experiments, respondents might not have considered the car to offer a relevant alternative, unlike the bicycle. Another influential factor could be the convenience of parking with a MSS compared to a private car. For respondents that own both car and bike the effects partially cancel-out each other, leaving them at an intermediate level with a greater likelihood of choosing MSS compared to individuals who own neither car nor bike.

4. Model application

We apply the estimated MNL model to explore the potential market share of MSS under a wide and diverse range of scenarios. The reference scenario serves as the baseline, wherein the values are derived from the sample averages. The market share of all other mode alternatives is estimated based on the share o the opt-out alternative included in the survey.

Firstly, we concentrate on investigating the market share for MSS considering the trade-off between ride fee and walking time, with all other variables held constant. The heat map depicted in Fig. 5 illustrates how the higher the ride fee and the longer the walking time become, the smaller the market share of MSS is. This reveals the potential for operators to dynamically vary the ride fee based on vehicle location in relation to user's location, thereby influencing vehicle choice accordingly.

Secondly, we examine the market of MSS under seven scenarios. In the following we provide a concise explanation of how each scenario differs from the reference scenario. The specification of attribute values is detailed in Table 3.

Scenarios:

1. **Market flooding:** This scenario represents a service area with

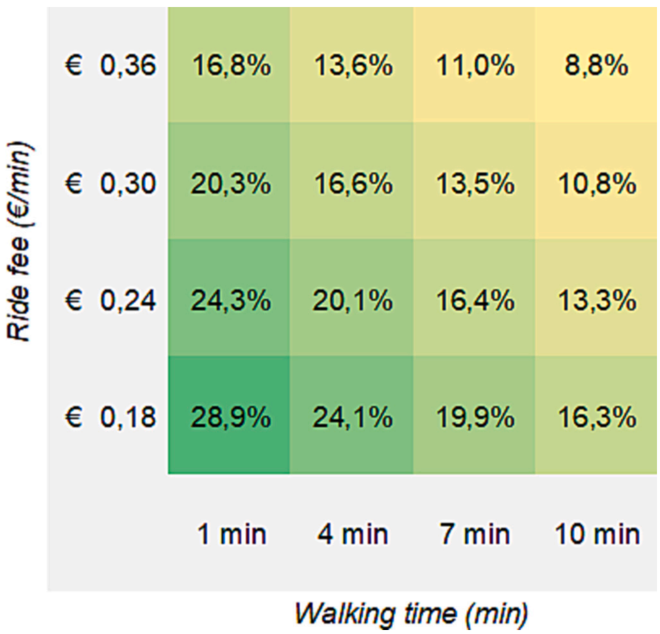

Fig. 5. Heat map of market share for MSS considering all ride fee and walking time levels.

affordable and easily accessible vehicles. Users encounter short walking times (high density in area) with vehicles available en-route to the destination.

2. **Limited but premium service:** This scenario represents a service area with expensive and lower availability of vehicles. Users encounter long walking times (low density in area) with vehicles off-route to the destination.

3. **Small-sized wealthy community:** This scenario depicts a service area situated within a small village characterised by a high income community. The travel distances within this area are relatively short, and the income level surpasses €4000, corresponding to income level 4–5. Furthermore, there is a notable prevalence of car ownership in this community.

4. **Beach trips:** In this scenario, we investigate leisure trips originating from non-home locations near a transportation hub, such as a train station, facilitated by a high availability of vehicles. The scenario revolves around long-distance trips, in sunny weather conditions (no precipitation).

5. **Blue collar workers:** Catering for the travel patterns of blue-collar workers, who typically fall within the income range below €2000 (income level 1–2). They undertake longer trips originating from home.

6. **Periphery to city centre:** This scenario investigates trips starting from lower income areas on the outer periphery of the city towards the city centre. The focus is on uncovering the market in low-income brackets with a lower car ownership rate.

7. **45 km/h type only:** This scenario explores the market share for MSS without the presence of 30 km/h vehicles. The focus is on understanding the impact when users are restricted to vehicles with a speed of 45 km/h, where wearing a helmet is obliged.

Table 4 presents the market share for MSS for the reference scenario and for each of the other seven scenarios. The market share in the reference scenario is 16,5%, which is considered to closely align with real-world conditions, given that the model reflects the preferences of surveyed moped users. Furthermore, the market share for the reference scenario is comparable to the findings reported by Loudon, Geržinič, Molin, and Cats (2023) which revealed a market share of 20.2% for MSS when considered alongside the car and bicycle (for users and non-users of MSS). This provides confidence in the model estimation results.

Scenarios 1 and 2 demonstrate the expected market trends when MSS availability is manipulated, with scenario 1 representing market flooding and scenario 2 corresponding to limiting the supply by offering MSS as a premium service. The results indicate that the adoption of MSS is likely to be higher when there is an abundance of vehicles available at

Table 4
Moped Sharing System market share for different scenarios.

No.	Scenario	MSS market share
0	Reference	16,5%
1	Market flooding	31,2%
2	Limited premium service	7,9%
3	Small sized wealthy community	7,3%
4	Beach trips	33,7%
5	Blue collar workers	29,2%
6	Periphery to city centre	23,3%
7	45 km/h type only	13,6%

Table 3
Scenarios and attribute values.

Attributes	Scenario name							
	Reference	Market flooding	Limited premium service	Small-sized wealthy community	Beach trips	Blue collar workers	Periphery to city centre	45 km/h type only
Ride fee (€/min)	€0.27	€0.18	€0.36	€0.27	€0.27	€0.27	€0.27	€0.27
Walking time (min)	5.5 min	1 min	10 min	5.5 min	5.5 min	5.5 min	5.5 min	5.5 min
Vehicle type (30 km/h/45 km/h)	50%/50%	50%/50%	50%/50%	50%/50%	50%/50%	50%/50%	50%/50%	100%/0%
Vehicle location (en-route/off-route)	50%/50%	100%/0%	0%/100%	50%/50%	100%/0%	50%/50%	50%/50%	50%/50%
Trip purpose (leisure/commuting)	50%/50%	50%/50%	50%/50%	50%/50%	100%/0%	0%/100%	50%/50%	50%/50%
Trip start location (home/not home)	50%/50%	50%/50%	50%/50%	50%/50%	0%/100%	100%/0%	100%/0%	50%/50%
Precipitation (dry/rain)	50%/50%	50%/50%	50%/50%	50%/50%	0%/100%	50%/50%	50%/50%	50%/50%
Trip distance (km)	4 km	4 km	4 km	2 km	7 km	7 km	5 km	4 km
Gender (female/not female)	35%/65%	35%/65%	35%/65%	35%/65%	35%/65%	20%/80%	35%/65%	35%/65%
Income level 1/2/3/4/5	12%/19%/35%/15%/18%	12%/19%/35%/15%/18%	12%/19%/35%/15%/18%	0%/0%/0%/50%/50%	12%/19%/35%/15%/18%	10%/90%/0%/0%/0%	30%/50%/20%/0%/0%	12%/19%/35%/15%/18%
Car ownership (%)	67%	67%	67%	100%	67%	67%	50%	67%
Bicycle ownership (%)	81%	81%	81%	81%	81%	81%	81%	81%

low prices (compared to other transportation modes). Conversely, limiting the supply of MSS as a premium service results in a decrease in its adoption. These findings underscore the significance of vehicle availability and pricing as crucial factors influencing the adoption of MSS as a preferred mode of transport as well as offer boundary conditions - upper and lower bounds - for its market share under a variety of circumstances.

Scenarios 3, 4, 5, and 6 provide valuable insights into the extent to which specific trip characteristics and socioeconomic factors influence MSS market share. Notably, these scenarios, particularly scenarios 3, 5, and 6, also highlight the impact of income levels on MSS usage, i.e. higher income levels leading to a reduction in MSS adoption. These findings offer valuable implications for policymakers and operators aiming to tailor their services to different user segments and optimise MSS adoption in diverse contexts.

Scenario 7, as a stand-alone scenario, demonstrates a reduction in market share of 2.9% for the 45 km/h vehicle type when compared to the reference scenario. As mentioned in the previous section, this reduction is assumed to be attributed to the dislike for wearing helmets and the obligation to use the road, as opposed to bicycle lanes. This finding provides insights into the potential impact of policies introduced by local or national governments on the adoption and acceptance of specific vehicle types and the adoption and usage of shared mobility services.

5. Conclusion

Free-floating vehicle sharing systems are becoming increasingly popular and provide new means of travel, especially within urban areas. These free-floating vehicle sharing systems offer the flexibility of one-way transportation. At the same time, the downside of this flexibility is that it creates a spatial-temporal imbalance of the vehicle distribution within the system. Studies regarding this one-way configuration so far mainly contributed with (theoretical) optimisation strategies to improve system performance. Moreover, there is only a limited number of studies that focus on users' behaviour, in particular vehicle choice, and consequently limited knowledge on the implications thereof for the potential performance of user-based relocation strategies.

We investigated vehicle choice in relation to an array of user-specific, alternative-specific and context-specific attributes. To our knowledge this is the first study that enables the assessment of pricing strategies by identifying the value of ride fee savings. This is achieved by means of a stated choice experiment among users of an e-moped sharing system which enables eliciting individual choice preferences.

The behavioural experiment provides crucial insights into the factors influencing users' perception of MSS and their vehicle choice under different circumstances. In general, the estimated parameters for the shared e-moped attributes ride fee (€/minute), walking time (minutes), vehicle type, and vehicle location all show the expected signs. The results show a dislike for higher ride fees and walking times the trade-off implying respondents require a reduction of €0.02 of the ride fee for each additional walking minute to access a vehicle. Respondents also show a preference for the 30 km/h type e-moped and a preference for vehicles that are located en-route to the final destination of the intended trip. The context variables showed that respondents had an increased preference for using shared e-mopeds compared to the opt-out options for leisure trips, not starting at home (activity-based trips), and during dry weather. The contribution to utility of an increasing distance peaks at five kilometres and then starts to drop.

We applied the estimated MNL model to gain valuable insights into the market share and therefore the adoption of MSS under a variety of scenarios and specific market segments, thereby enhancing the transferability of our findings. We analysed scenarios focusing on MSS availability, pricing, trip characteristics, and socioeconomic factors. The scenarios investigated demonstrate that the market share of MSS varies within the range of 8 to 33% with the lowest bound recorded for a limited premium service provision and the highest bound registered for trips between a transportation hub and the beach. An analysis of the scenarios highlights the importance of specific trip characteristics and income levels in influencing MSS usage. These findings offer essential implications for policymakers and operators aiming to tailor MSS services to diverse user segments and optimise adoption in various contexts.

Based on these findings, variable pricing levels could influence vehicle choice if price levels were to be adjusted dynamically based on the location of vehicles in relation to the user location. This pricing mechanism can also be used to stimulate demand under various circumstances. For example, users might use shared e-mopeds more often during rainy weather if the ride fee (€/minute) is reduced to compensate for the bad weather conditions. A mobility service provider is likely to introduce such a dynamic pricing strategy only when it results in increased system and consequently revenue performance.

Our findings are likely to be applicable for other vehicle sharing systems with the same design and management configurations. Since our sample is composed of current users of a shared e-mopeds operator, the results may not reflect the perceptions of non-users. Future research may target non-user groups in order to examine whether potential new users might exercise different trade-offs. Moreover, the choice model estimates do not account for panel effects and taste variations.

One of the main limitations of stated choice data in general is that it subject to a hypothetical bias, i.e. respondents' choices may not correspond with their actual preferences. This mainly results from the fact that the consequences of choices are not felt and that new attribute levels are not yet experienced in real-world situations. Therefore, further research could focus on analysing observed vehicle choices. Data from observed choices may become available from field implementations of pricing schemes, thereby enabling the empirical analysis of user choices in relation to applied pricing strategies in shared fleets.

CRediT authorship contribution statement

Tom Hoobroeckx: Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Oded Cats:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing, Funding acquisition. **Sanmay Shelat:** Methodology, Supervision, Writing – review & editing. **Eric Molin:** Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest in relation to this work.

Data availability

The authors do not have permission to share data.

Acknowledgments

We thank felyx sharing for facilitating survey dissemination among their users. The work of the second author is supported by the CriticalMaaS project (grant number 804469), which is financed by the European Research Council and the Amsterdam Institute for Advanced Metropolitan Solutions.

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