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# Willingness to pay and trading behaviour of mobility credits

Nejc Geržinič *, Oded Cats

*Department of Transport and Planning, TU Delft, Delft, the Netherlands*

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ABSTRACT

Tradeable Mobility Credits (TMC) are a novel demand management policy. Travel can be priced based on externalities and travellers are allocated TMC, which are consumed when travelling, with the price depending on trip characteristics. Travellers can buy/sell TMC in exchange for money. In this study, we analyse (1) how travel behaviour would be affected by a TMC-scheme, (2) TMC trading behaviour and (3) their interaction. We carry out an online stated preference survey, and apply a latent class choice model (LCCM) to analyse travel behaviour, whereas credit trading is analysed by means of a multiple linear regression. A key finding throughout the research is that TMC tend to be perceived non-linearly, with a logarithmic transformation often outperforming linear specifications. This means each additional credit carries less value. The LCCM reveals three out of four groups (88 % of respondents) consider their current balance when making travel choices. Two groups (~50 %) are predominantly unimodal, travelling almost exclusively by bicycle or public transport. Others base their decision primarily on travel time and cost. In trading, the exchange rate and balance have a substantial influence, offering evidence for loss aversion. The number of travel instances remaining, and the experience of having performed a trade in the past also affect trading behaviour, whereas socio-demographic characteristics are found to have a limited impact. Our result show a TMC policy can achieve substantial behavioural adaptations, reaching the desired outcomes. The limited awareness of such policies, concerns about equitable TMC allocation and additional hassle associated with trading remain challenges to be addressed.

## 1. Introduction

Traffic congestion, air and noise pollution, as well as road safety concerns, resulting from high car use, have been the driving force of a vast array of travel demand management (TDM) policies. Broadly, these policies can be divided into pull methods (improving alternatives to using private cars, i.e. better public transport (PT), cycling infrastructure,…) and push methods (various pricing measures or access restrictions). Research shows that pull policies tend to have higher public and political acceptance, but result in a substantially lower reduction in car use (Gärling and Schuitema, 2007; Schlag and Schade, 2000).

A TDM measure that is gaining traction and attention is Tradeable Mobility Credits (TMC). Through this policy, people are allocated a certain number of credits for a given time period (i.e. a day, week, month) for their mobility needs. They then spend these credits through travelling, with an authority determining the travel price (in TMC) based on the desired effect of the policy. A key merit of TMC over other TDM policies is in the possibility of trading. Users may sell surplus credits, giving them a financial incentive to adjust their behaviour, or buy additional credits if required. Although in many cases, conventional pricing TDM policies outperform TMC, a major advantage of the latter is application. Policymakers merely have to set the desired /expected outcome which is guaranteed through the trading among users, whereas in TDM policies, more advanced computational techniques are required to define the optimal price for a desired outcome (Geng et al., 2025). For a detailed overview on different approaches and implementation strategies of a TMC policy, analysing TMC allocation, trading, the role of a public authority, etc., the reader is referred to the overview and classification of TMC schemes by Provoost et al. (2023).

A second potential benefit of TMC is their ability to act as both a pull and push approach, integrating the penalising side through pricing and the rewarding side through remuneration and lower price of alternative travel modes. This is shown to also increase the public acceptance of TMC over other traditional TDM measures (Brands et al., 2020). Yet despite these potential advantages, research relating to TMC schemes focused almost exclusively on car route choice or parking behaviour (Aziz et al., 2015; Balzer et al., 2023; Bao et al., 2020; Brands et al., 2020, 2021; Dogterom et al., 2017; Fan and Jiang, 2013; Lessan and Fu,

* Corresponding author.
*E-mail addresses:* n.gerzinic@tudelft.nl, nejcgerzinic@gmail.com (N. Geržinič).

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2022) rather than mode choice effects. The potential for mode-switching behaviour, a key aspect of TMC policies, has seen limited attention, with, to the best of our knowledge, Dogterom et al. (2018) and Álvarez-Ossorio Martínez et al. (2025) being the only ones to also include other modes in investigating travel behaviour effects of TMC.

Both studies (Álvarez-Ossorio Martínez et al., 2025; Dogterom et al., 2018) used a survey-based data collection approach, with the Dogterom et al. (2018) carrying out a stated adaptation experiment, and Álvarez-Ossorio Martínez et al. (2025) a stated choice experiment. In their study, Dogterom et al. (2018) asked respondents to report a week's worth of car trips. Thereafter, they were presented with two different TMC scenarios (successively), first a more modest pricing level, followed by a stricter, more ambitious scenario. The cost of travel was adjusted and the respondents given the opportunity to make changes to trips, i.e. cancelling, adding, rescheduling or changing the mode (to public transport, active modes or carpooling). Interestingly, the first target (17.5 % reduction of vehicle-kilometres travelled) was exceeded (~20 %), while the second target of a 32.2 % reduction was not met (only 24 %). Specifically, almost half of all respondents did not make additional changes between the first and second scenario and were willing to absorb the additional charges. Through a binary logit model, the authors report that younger respondents and those with more children were more likely to reduce car use, whereas those with a lower income or living in more rural areas were less likely to do so.

A more traditional stated preference mode choice survey was carried out by Álvarez-Ossorio Martínez et al. (2025) in Munich, Germany. They compare the most frequently used modes (walking, cycling, car, PT) on price and various travel time aspects for PT (walking, waiting, transfers) in two different scenarios, namely without and with TMC (termed MobilityCoin by the researchers). In the scenario with TMC, those are specified in actual currency units (€) rather than as it's own unit, and specified separately from the direct cost of travel. In addition, the respondent's remaining budget (for the rest of the month) and the time left in the month were presented. The authors report that respondents tended to be more sensitive with a lower budget or with a longer time left within the month. They also show that willingness-to-pay becomes much higher when accounting for respondent heterogeneity, with values around the 30–40 €/h range.

The trading of TMCs remains a topic with limited attention, with only a handful of studies analysing the trading behaviour of travellers or respondents (Aziz et al., 2015; Brands et al., 2020, 2021; Geng et al., 2023). Among these, Aziz et al. (2015) were the only ones to develop a separate trading model that predicts buying and selling of credits (bids and asks in their double auction approach). The other articles provide insightful descriptive statistics and/or incorporate trade-related parameters into the travel choice model. In their results, Aziz et al. (2015) highlight that participants with more money and those using more credits were more likely to buy credits. In the listed studies, price also tended to have the expected effect, resulting in buying credits when prices were low and selling when high. Brands et al. (2020) also report that respondents, on average, ended with a surplus of money, meaning they traded in the right moments, buying when price was low and selling when high, to end with a profit. Both Brands et al. (2020) and Brand et al. (2021) report that the system was clear and understandable to respondents, although admit that it was a biased sample of "experienced commuters" who also actively participated to take part in experiments.

Summarising the literature review above, to the best of our knowledge, only two studies investigated mode choice behaviour under the premise of TMC (Álvarez-Ossorio Martínez et al., 2025; Dogterom et al., 2018), while not accounting for the trading of TMC, and only one study (Aziz et al., 2015) analysed the credit trading behaviour of travellers in the context of route choice behaviour. Our paper therefore contributes to this body of knowledge by addressing a persisting knowledge gap related to trading and travel behaviour in the presence of TMC schemes. Specifically, we collect behavioural data, analyse and estimate (1) mode choice trade-off behaviour under the premise of a TMC scheme, (2) credit trading behaviour of individuals and (3) the interaction between the two, i.e. how the credit trading market and travel price in credits affects mode choice behaviour and vice versa. The rest of the chapter is structured as follows: the survey setup and wider context of how the therein envisioned TMC system would be designed is presented in Section 2. The behaviour modelling of mode choice and credit trading is discussed in Section 3. Section 4 then describes the data collection approach as well as presents the first insights and descriptive statistics of the survey sample. Section 5 then dives deeper into the mode choice results, presenting the modelling outcomes, while the outcomes of the trading models are presented in Section 6. An example application and discussion of the outcomes are shown in Section 7. Finally, the paper is concluded, with policy implications and future research outlined in Section 8.

## 2. TMC setup and survey design

To collect behavioural data of individuals, we carry out a stated preference (SP) discrete choice experiment among the urban population in the Netherlands. An SP approach to data collection is adopted since TMCs are a hypothetical policy measure and thus collecting quantitative data from actual usage is infeasible. Additionally, an SP approach allows us to control and vary the attributes within the experiment to obtain sufficient variation and avoid correlation effects among attributes. The survey is designed in Ngene software (ChoiceMetrics, 2021).

Respondents start the survey with a predefined number of credits (starting budget) and a neutral money budget (€0), both of which update throughout the survey, based on usage (travel) and credit trading. In each choice situation, respondents are presented with travel options, the current credit balance, accumulated expenses and the current exchange rate. Before choosing a travel mode, they have the option to buy or sell credits at an exchange rate that is available in that moment. A full example is provided in Fig. 1.

We apply a strict limit that the TMC budget cannot be negative. Respondents could not select a travel mode that cost more TMC than they had available at that time. Instead, respondents could either choose a more affordable mode or buy additional credits. With respect to the money budget, no such limit was enforced. Implementing a limit on the money budget could result in complications where some respondents could not be able to finish the survey due to reaching the limits in both their TMC and money budgets.

As the experiment takes place online and respondents do it at their own time and pace, we assume a TMC scheme where individuals trade with an intermediary, i.e. TMC bank and not directly with each other. Since TMC are a fictional payment unit, no upfront value can be used, and the value does not have a direct meaning in absolute terms. For example, if 1TMC = €1.00, the price of a public transport trip may be 3TMC. But if the value is set to 1TMC = €0.10, the PT trip would be priced at 30TMC. The travel costs are therefore based on the exchange rate of TMC which is a consequence of market decisions. Irrespective of its worth, the ratios between different modes need to be consistent and based on the cost of their respective externalities. How TMC exchange rates are determined is outlined in Section 2.2.

Lastly, since SP data collection is inherently hypothetical, one option of making it more tangible is to remunerate respondents based on their performance in the survey. This would give them an incentive to be more watchful of their budgets as it would have actual implications for them. The downside however is that a higher survey payout may become the key (or sole) objective, and the exhibited behaviour would be less realistic. To avoid this potential risk, we opt for equal remuneration of all respondents, regardless of their performance in the survey. Additionally, we make it explicitly clear in the introduction that there are no right and wrong answers, and that we ask them to make the same choices as they would if a TMC scheme would have been implemented.

In the remainder of this section, the setup of the mode choice part of the experiment is detailed in Section 2.1. Thereafter, the trading aspect

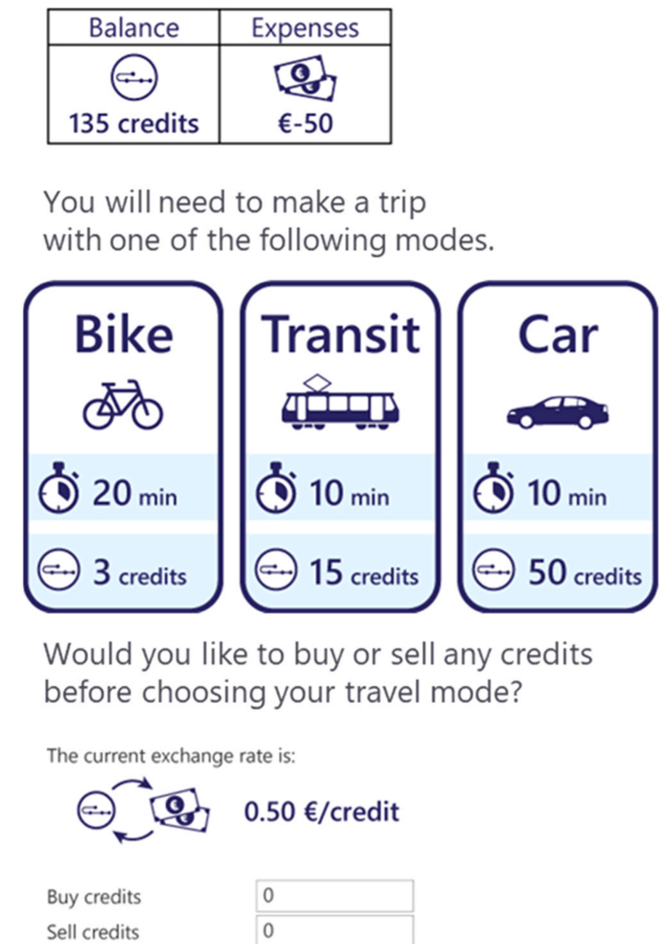


**Fig. 1.** Example screen from the survey.

of the experiment, including determining the starting budget and variation of the TMC exchange rate are elaborated upon in Section 2.2. Finally, additional data collected during the survey is discussed in Section 0.

### 2.1. Mode choice

The first part of the SP experiment is the mode choice component. Through this, we wish to gain a better understanding of people's preferences and willingness-to-pay (WtP) for different modes and travel time improvements, particularly in urban areas. Although TMC can be applied on an urban, regional, national or even international level, our focus is primarily urban, as most research on the topic has so far focused on it and it is where most benefits of a TMC scheme are expected. Given this, we specify that the trip in question is in an urban area and one the respondent makes often. Additionally, we specify the weather conditions to be dry and ~15 ° Celsius. We do not provide an explicit trip purpose (work, leisure) as to not limit the transferability of our results, while testing both is excluded due to the increased complexity this would bring with it.

As the concept of tradeable mobility credits is new and most respondents will be unfamiliar with it, our aim is to keep the experiment as simple as possible. To that end, we include three travel modes, namely the bicycle, PT and car, since these are the most commonly used modes in Dutch urban areas, each making up around 1/3 of the total modal split (City of Amsterdam, 2018). We choose not to provide an "opt-out" option, as our goal is to study the behaviour concerning necessary trips.

Each mode is then described by two attributes: travel time and travel cost. A single travel cost attribute, expressed in TMC units is implemented for the sake of simplicity and to avoid excessive cognitive burden on the respondents. This means that the direct cost of travel (PT ticket, fuel, parking…) is combined with the indirect cost and presented to the respondents as a single travel cost, in TMC units.

Next we determine the levels of both attributes. To allow testing for non-linearity, we specify three attribute levels for both while also observing equidistance between levels. Travel time represents the total door-to-door travel time, including any potential walking time, waiting time and parking search time. We use Google Maps, to determine possible travel time values for all three modes. Again to keep the survey simple, we use the same three levels for all three modes, which is deemed realistic for trips in larger Dutch cities.

Travel cost is calculated based on the work of Brand et al. (2021), who researched the emissions associated with different travel modes per passenger-kilometre, including both direct operating emissions as well as emissions from the production and maintenance. Specifically, we use the emission ratios between the three analysed modes from the study. The resulting ratios vary substantially between cities, which we are able to incorporate into the SP survey through different attribute levels, capturing as wide of a range of the ratios as possible. Since production and maintenance is also included in their study, Brand et al. (2021) also associate cycling with a certain, albeit low, amount of emissions, partly from bicycle production and partly from electricity being used to power e-bikes. In addition to that, TMC can also be applied based on other external effects, not only emission. They can be utilised as a tool to incentivise desirable ways of travel and vice-versa. To that end, we also test a non-zero TMC cost for cycling. While this may be counterintuitive, we wanted to test how a potential cycling-oriented policy is perceived. The values are still very low in comparison. The final overview of attribute levels per mode is given in Table 1 and an example of the choice set is provided in Fig. 1. As there are very few studies available on the topic and to avoid any bias in survey design, we opt for an orthogonal design with 12 choice sets. The final design is presented in Table 14 in Appendix A.

### 2.2. Credit trading

The second aspect of the experiment is the use and trading of TMC. Having determined the travel cost of individual modes based on their externalities (emissions), we now need to determine how many credits we assign to respondents. This can be accomplished by utilising one of the policy's key benefits, namely by setting how many credits are circulating in the system, the desired outcome of meeting the target (or better) can be guaranteed. In this case we use a target modal split of the city of Amsterdam as a proxy for all Dutch urban areas, which in combination with the average cost of each mode, results in the starting budget required for the 12 trips. To test how TMC scarcity affects behaviour, we specify three different starting budgets. The highest of 350TMC corresponds to the current modal split, the lowest budget (150TMC) to the 2030 target modal split (City of Amsterdam, 2018) and the middle value (250TMC) as the midpoint between the two. For the survey, this results in three separate starting budget blocks. We elaborate on how these values were obtained in Appendix B.

Next, we specify another key characteristic of a TMC policy, the trading. As mentioned previously, the respondents are expected to fill in the survey at their own convenience, meaning that a dynamic exchange rate, typically based on multiple hypothetical traders buying and selling credits is impractical in this situation and basing the variation on the actions of a single trader can quickly become too predictable. Instead,

**Table 1**
Alternatives, attributes and attribute levels.

| | Bicycle | Public transport | Car |
|---|---|---|---|
| Travel time [min] | [10, 20, 30] | [10, 20, 30] | [10, 20, 30] |
| Travel cost [TMC] | [1,2,3] | [5, 15, 25] | [40, 60, 80] |

we predefine the exchange rate exogenously for all 12 choice sets. By combining data on individuals' monthly mobility expenditure in the Netherlands (Koopal et al., 2018) (adjusted for inflation) and the average number of short urban trips in the Netherlands (de Graaf, 2015), we obtain the average expenditure per trip, namely: 4.37€/trip. Next, we use the three different starting values to determine the average expenditure of TMC/trip, which, combined with the previous price per trip, enables us to determine the exchange rate (€/TMC) for each of the three scenarios, as shown in Table 2.

The obtained average exchange rates are used to create three exchange rate scenarios. As stated earlier, the exchange rates per choice task are determined upfront. This is done by using the average exchange rates from Table 2 as the statistical mode of a log-normal distribution of exchange rates. A log-normal distribution is used as it can easily be restricted to positive values only while also allowing for the occurrence of occasional high exchange rates. To make trading more attractive to respondents (potential for a higher reward), the previously calculated modal exchange rate values are doubled, which results in wider exchange rate distributions to draw from. In addition to increasing the reward potential for selling, this also makes the potential penalty for exceeding the budget higher. The distributions used are shown in Fig. 2, with mean and mode values, and the exchange rates used in each choice situation presented in Table 3.

In order to test how different levels of exchange rate volatility or variability affect behaviour, we do not link the exchange rate block to the starting budget block that was used to construct it. Instead, the respondent is randomly assigned to one starting budget block and one exchange rate block. This results in a total of nine starting budget-exchange rate combinations

### 2.3. Attitudinal and socio-demographic information

Finally, we gather respondents' attitudes on financial matters, their current travel behaviour and socio-demographic information. The mechanism and concept of trading credits represents a substantial departure from the way people experience travelling today, so to better understand if their trading behaviour may be influenced by their financial literacy and risk-taking behaviour in making financial investments, we pose 12 attitudinal statements in relation to financial matters, people's behaviour, personality, confidence and attitudes towards risk and returns. Respondents can indicate the level of their (dis) agreement through a 5-point Likert-scale. The 12 attitudinal statements, based on research by Zheng (2013), are:

1. I usually have tight control over my budget for major spending.
2. I do not like buying stocks simply because of the risks involved.
3. I prefer investments that do not involve risks.
4. I am not interested in making a lot of money.
5. I always view risks as losing money.
6. I prefer safety to risk in financial investment.
7. I understand risk may be good, but I consider it as negative.
8. Greater risk leads to higher rates of return.
9. I do not believe I have the talent to manage my investments.
10. I do not worry about my financial choices.
11. I am usually quite stressed about making a big daily financial investment decision.
12. Financial investment in general is very stressful to me.

**Table 2**
Determining the average exchange rate per starting budget scenario.

| Price per trip | 4.37€/trip | |
|---|---|---|
| Starting budget | TMC per trip | Exchange rate |
| 150 TMC | 12.50 TMC/trip | 0.35€/TMC |
| 250 TMC | 20.83 TMC/trip | 0.21€/TMC |
| 350 TMC | 29.17 TMC/trip | 0.15€/TMC |

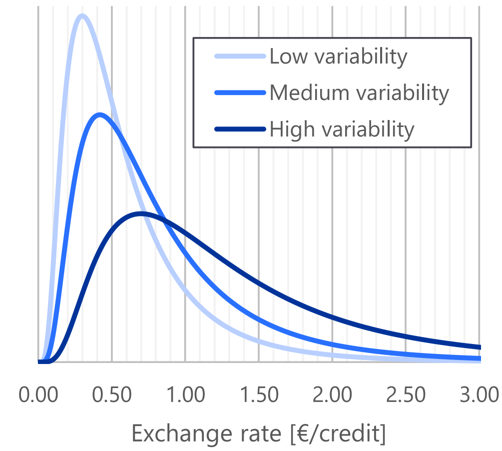


**Fig. 2.** Log-normal distributions of different exchange rate scenarios.

**Table 3**
Exchange rates and distribution characteristics (all values in [€/credit]).

| | | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| Mode | | 0.30 | 0.42 | 0.70 |
| Mean | | 0.60 | 0.84 | 1.40 |
| Choice situation | 1 | 0.40 | 0.70 | 1.10 |
| | 2 | 0.30 | 0.70 | 1.90 |
| | 3 | 0.30 | 0.60 | 4.90 |
| | 4 | 1.00 | 0.40 | 0.60 |
| | 5 | 0.20 | 1.80 | 1.30 |
| | 6 | 1.20 | 1.10 | 2.30 |
| | 7 | 0.40 | 2.20 | 0.80 |
| | 8 | 0.40 | 0.60 | 0.90 |
| | 9 | 0.30 | 0.60 | 0.30 |
| | 10 | 0.20 | 0.40 | 1.30 |
| | 11 | 0.60 | 0.50 | 1.50 |
| | 12 | 0.60 | 1.20 | 0.10 |

On the topic of travel behaviour, we collect information on respondents' modal preferences for different trip purposes, the frequency of using each mode, household car ownership and driving licence ownership. For socio-demographic information, we ask respondents to report their gender, age, income, completed level of education, working situation, city in which they reside, household size and household composition.

## 3. Behavioural modelling

To analyse the obtained behavioural data, two different modelling approaches are employed, namely for the mode choice observations and for the credit trading, both of which are described in the following two subsections, respectively

### 3.1. Mode choice modelling

The mode choice data is gathered through a traditional stated preference discrete choice experiment approach and is thus modelled by means of a discrete choice model (DCM). To test if respondents utilise a utility maximising or regret minimising decision rule, we estimate a μRRM model (Van Cranenburgh et al., 2015). By means of an additional parameter (μ) we are able to determine what the underlying decision rule is with a value close to 0 indicating a regret minimisation approach whereas values above 10 suggest utility maximisation behaviour.

Next, we specify a series of interaction effects and model formulations to assess the potential impact of credit-related aspects of mode choice under a TMC-scheme. Firstly, we test if travel costs are perceived as they are presented (in TMC) or do respondents convert them into monetary units (Equation 1). This is done for the current exchange rate as well as considering past exchange rates, if individuals perhaps keep a mental record of past experiences. Secondly, we specify a series of traditional interaction effects (Equation 2), where we test if context or socio-demographic attributes have an impact on the perception of attributes from the choice task.

Equation 1. Specification of the cost conversion from TMC to money (€)

$$\beta_K \bullet (X_{Kc} \bullet r_c)$$

Where:

$\beta_K$ parameter for attribute $K$

$X_{Kc}$ attribute level of attribute $K$ in choice task $c$

$r_c$ exchange rate in choice task $c$

Equation 2. Interaction effect model specification

$$(\beta_K + \beta_{AK} \bullet X_{Ac}) \bullet X_{Kc}$$

Where:

$\beta_{AK}$ interaction parameter of attribute $A$ on parameter attribute $\beta_K$

$X_{Ac}$ attribute level of attribute $A$ in choice task $c$

We assess the impact of different interaction effects based on the significance of the interaction parameter, the improvement in model fit (Log-likelihood or LL), the likelihood ratio test (LRT) and the BIC value. The level of significance conveys if the impact of the parameter on the overall model is notable. The model fit (LL) is certain to improve with an additional parameter, so the LRT and BIC help us in assessing if the improvement is big enough to justify an additional parameter. The LRT does so by comparing the model fits of two nested models, based on the chi-squared value (King, 1989), whereas the BIC is a static of each model and the model with the lower BIC is more parsimonious (Schwarz, 1978).

To account for respondent heterogeneity, we expand the model into a Latent Class Choice Model (LCCM) (Greene and Hensher, 2003). We opt for the LCCM rather than a mixed logit (ML) model, another common modelling approach accounting for heterogeneity, as it results in clear and distinct population segments. The LCCM allows us to incorporate socio-demographic characteristics into the class membership function of the different classes. We are then able to use this to predict the probability of each individual for belonging in a certain class. In turn, by determining the probability of each respondent belonging to a specific class, we are able to calculate posterior-weighted covariate means of socio-demographic characteristics for each class.

The downside of LCCM compared to ML is that they tend to utilise a substantially higher number of parameters and the model estimation is also prone to getting stuck in local maxima. To overcome this issue the model is estimated ten times, with different starting values, in order to minimise the likelihood of the model outcome being a local optimum. The model specification for each of the classes is based on the previously estimated interaction effects and how the individual models performed with respect to the BIC value and LRT test.

### 3.2. *Credit trading behaviour*

To analyse the outcomes of how many, if any, credits respondents bought or sold in each instant, a multiple linear regression model is employed. By testing a wide array of attributes, this enables us to assess the importance of each of them and the impact they have on the number of credits traded.

Firstly, different transformations of the dependent variable are tested. The direct option is a simple linear formulation, where values above 0 indicate how many credits are bought and values below 0 indicating the number of sold credits. To avoid potential issues with extreme trading amounts, we also test different truncations of the linear specification. Finally, as the perception of credits may be non-linear (i.e. the more credits one has or trades, the less each individual credit is worth), we employ a natural logarithm transformation. To avoid the problem that a logarithmic transformation cannot be carried out for negative values, we specify it as a negative value of sold credits. Additionally, as the resulting value of a logarithmic transformation is negative for inputs between 0 and 1, we add 1 to all values of traded credits. The formulation can be seen in Equation 3 and the visualisation of the five transformations in Fig. 3.

Equation 3. Logarithmic transformation of traded TMC

$$TMC_{\ln} = \begin{cases} \ln(TMC + 1) \text{ if } Y \geq 0 \\ -\ln(-TMC + 1) \text{ if } Y < 0 \end{cases}$$

Among the independent variables, two potentially important ones are the exchange rate and the individual's current credit balance. As both can be perceived in a variety of ways, we test different specifications to determine which explains best the observed choices. For exchange rate, we use the current exchange rate ($r_c$), the average of all past exchange rates ($\bar{r}$) and the difference between the two, namely: $\Delta r = \bar{r} - r_c$.

For credit balance, we test four different specifications, three of which rely on what we term "expected balance". This is the balance that a respondent is expected to have at a certain point, given their starting budget and the number of travel instances that are yet to occur. In other words, it assumes an equal number of credits is expected to be used in each instance in a way that by the end of the experiment, the respondent has just consumed all initially allocated credits. For example, with a starting budget of 150 credits, the respondent is expected to still have 75 credits after six of a total of 12 choice tasks. The four balance specifications are thus the current balance before making the trade ($b_c$), the expected balance ($b'_c$), the difference between the two ($\Delta b = b'_c - b_c$) and the difference between the logarithms of each ($\Delta b_{\ln} = \ln(b'_c) - \ln(b_c)$). This last specification is again meant to test if the perception may be non-linear in the sense that a deviation of 10 credits from the expected value may not mean very much with 250 credits, whereas with 20 credits, 10 credits more or less carries much more importance.

## 4. Data collection

The survey was distributed through an online panel (PanelClix), among individuals living in the five largest urban agglomerations in the Netherlands (Amsterdam, Rotterdam, The Hague, Utrecht and Eindhoven), between 28.11.2023 and 02.01.2024. A total of 1053 complete responses are recorded. The data is filtered based on several criteria. Firstly, a lower bound (5 min) is set to remove speeders. Since the relation between the different questions of the experiment is crucial, a maximal response time of 30 min is also set to ensure that respondents are still conscious of this relation. This results in the removal of 30 speeders and 71 respondents above the 30 min mark. Next, we check for straightlining behaviour on the 12 finance-related attitudinal statements, removing 26 responses. Finally, eight are removed due to a calculation error in the survey platform.

One further respondent is removed as they participated in this experiment by trying to maximise their revenue, buying and selling millions of TMC. While such behaviour cannot be ruled out in a real-world situation, it is removed as it is a drastic outlier and substantially skews the data.

This results in 917 fully valid responses. Comparing the socio-demographics of our sample to those of the urban areas we aimed to capture (Table 4), the sample is overall fairly representative. We do observe somewhat of an overrepresentation of higher educated individuals (with a university degree), older individuals (above 50 years old) and larger households (with two or more people). With income, we see an underrepresentation of high earners, although due to the reluctance to report income, we cannot conclude that with certainty. Our sample also has a higher car ownership (0.9 per household) and driving licence rate (82 %) than the target population.

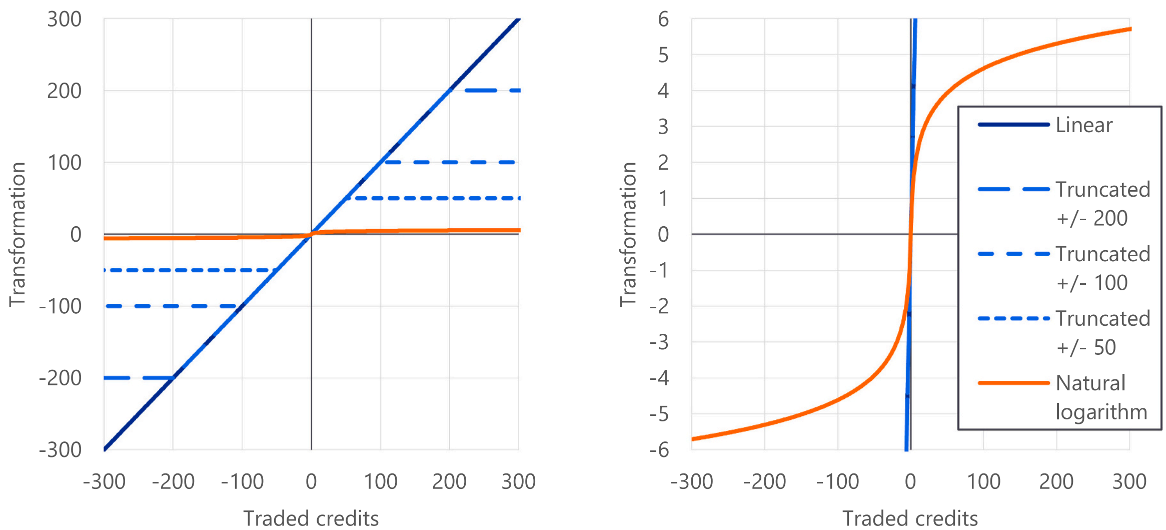


**Fig. 3.** Transformations of the number of traded credits, with a broader y-axis on the left and a zoomed-in y-axis on the right.

**Table 4**
Sample characteristics and representativeness.

| | | Sample | Population |
|---|---|---|---|
| Gender | Female | 51 % | 50 % |
| | Male | 49 % | 50 % |
| Age | 18–34 | 26 % | 36 % |
| | 35–49 | 23 % | 25 % |
| | 50–64 | 32 % | 22 % |
| | 65–120 | 19 % | 17 % |
| Education | Low | 12 % | 25 % |
| | Middle | 33 % | 33 % |
| | High | 55 % | 42 % |
| Income | < 30k | 22 % | 20 % |
| | 30–50k | 28 % | 21 % |
| | 50–100k | 27 % | 31 % |
| | > 100k | 9 % | 29 % |
| | n/a | 15 % | 0 % |
| Employment | Employed | 65 % | 55 % |
| | Retired | 17 % | 13 % |
| | Other | 18 % | 33 % |
| Household | Single | 31 % | 51 % |
| | More with kids | 31 % | 22 % |
| | More without kids | 37 % | 26 % |
| Car ownership | | 0.92 | 0.55 |
| Driving license | | 82 % | 67 % |

To provide some additional insight into the data before proceeding with the modelling, we highlight some descriptive statistics here, starting with the modal split. From Fig. 4, we can see that the bicycle dominated among all three starting budget blocks. Although higher shares of bicycle use can be observed among respondents with a smaller TMC budget, these shares are still higher than current modal splits. This can partly be attributed to all trips in the survey being bikeable (up to 30 min, in Dutch urban settings) and partly to hypothetical bias, as respondents do not have to directly experience the implications of their choices. An increased share of PT and car use by the respondents with more budget does indicate that a more restrictive TMC policy may result in more sustainable travel behaviour. Perhaps most striking is that in the 350-credit scenario, which is based on the current modal split (roughly $^{1}/_{3}$ for each mode), the outcomes vastly outperform this target, with over 60 % of choices being for bicycle.


**Fig. 5.** Number of trades made during the experiment.

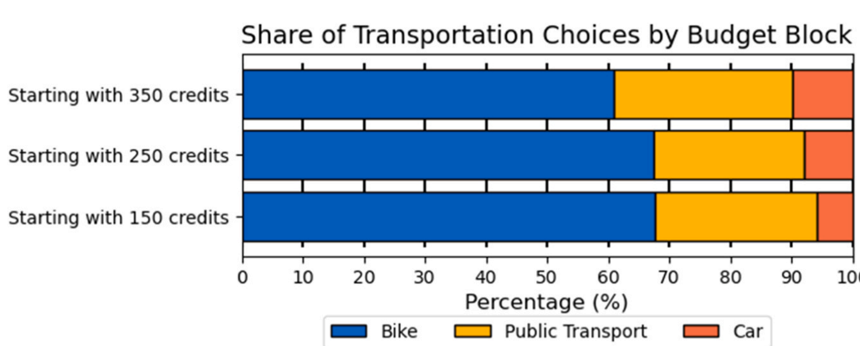


**Fig. 4.** Mode choice distribution among different starting credit blocks.

Moving to the trading behaviour, Fig. 5 shows that around 17 % of respondents did not make any trade during the experiment. Around 15 % traded in all 12 instanced and the rest are in-between. Looking at which specific instances saw trading (Fig. 6), we observe a that as the experiment went on, more people traded, with most being recorded in the last choice set. It is still important to note that overall, out of a total 11,004 trading opportunities (12 opportunities for each of the 917 respondents), less than half (42 %) were used, namely 2554 for selling and 2063 for buying.

Next, we analyse the amount of credits traded in those instances. Fig. 7 shows a histogram of individual trade amounts and how frequently those were observed. It shows that the majority of trading involved 100 credits or fewer, with the two most frequent being buying and selling 10 or fewer credits. Considering the total traded amount, we can observe in Fig. 8a similar trend to the one observed in Fig. 6, where more trading took place towards the end of the experiment, with the most bought and the most sold credits being recorded in the last choice task. Selling likely resulted from respondents selling what they had left, as they were informed (upfront) that credits would otherwise have expired. The buying could either stem from respondents having run out of credits and needing to buy more to travel, or from highly variable exchange rate block, who's exchange rate at the end was very low, making it potentially attractive to buy at a low rate. This is somewhat surprising, as the credits would have expired immediately after. The respondents may have assumed that would have another change after to trade and get rid of credits, they may not have been paying attention that it was the last instance already, or perhaps they forgot the fact the credits would expire and were tempted by the low exchange rate.

Looking at the balance evolution (Fig. 9), we see that, as expected, all groups have a general downward trend, using up credits as time goes on. Occasional upward ticks appear for the same exchange rate groups, indicating a potential low exchange rate and thus an interest in buying credits. Likewise, a sharper decline in balance corresponds to a high exchange rate, encouraging respondents to sell. As noted previously, respondents in the highly variable exchange rate group bought in the last instance due to the very low exchange rate. What is also noticeable from Fig. 9 is that many did not end with a final balance of 0, unlike what one might have expected.

In Fig. 10, we can see the end-state of both the credit balance and money balance. For credits, we do observe that for all subgroups, a plurality did finish with 0. What is also noticeable is that individuals with more starting credits were also more likely to finish with more. Although Fig. 4 shows that they spent more, they still did not spend enough to reach the balance level of those starting with fewer credits (Table 5). We observe that those starting with more credits finish with a higher balance and are less likely to have a money deficit at the end of the experiment. Combined with the mode choice results shown in Table 5, this suggests that those with more credits used credits both to travel with more polluting modes as well as to sell part of which to earn some extra money.

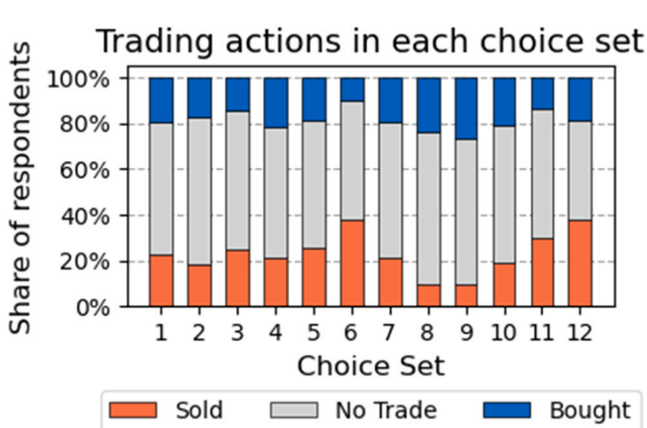


**Fig. 6.** The share of respondents trading in each choice set.

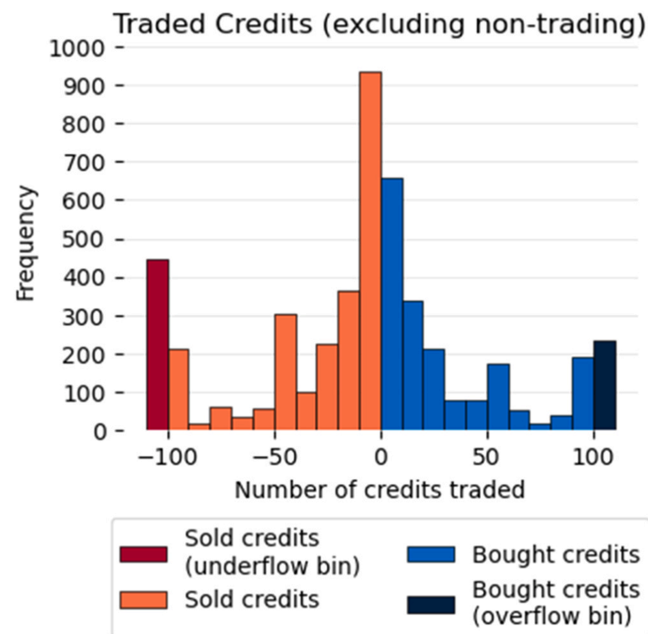


**Fig. 7.** Histogram of trading amount frequencies.

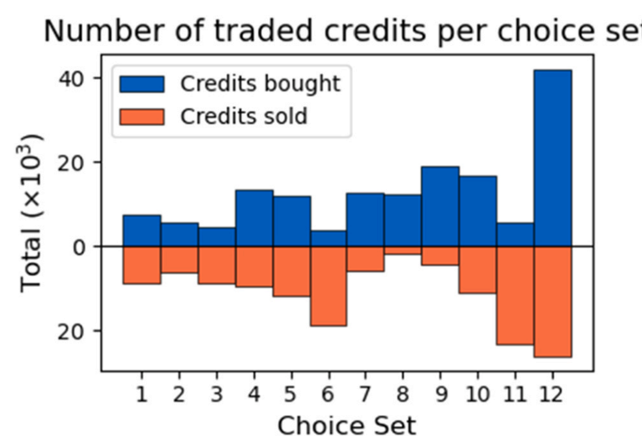


**Fig. 8.** Total amount of traded credits during each choice set.

## 5. Mode choice behaviour

To analyse the mode choice behaviour of respondents, a discrete choice model is employed, using the Biogeme software (Bierlaire, 2023). We start by estimating a series of multinomial logit (MNL) models, testing a variety of specifications and interaction effects, focusing specifically on the interaction with TMC-related characteristics such as credit balance and exchange rate. In the next step, we analyse how the perception of TMC and the Willingness-to-Pay (WtP) differs within the sample by estimating a series of LCCMs, with socio-demographic characteristics providing additional information on the composition of the individual groups.

### 5.1. Multinomial logit models

Firstly, we test the simplest form of an MNL model to determine the decision rule applied by respondents. Utilising the μRRM framework, the estimated value of μ, at 56, indicating a utility maximising behaviour, as

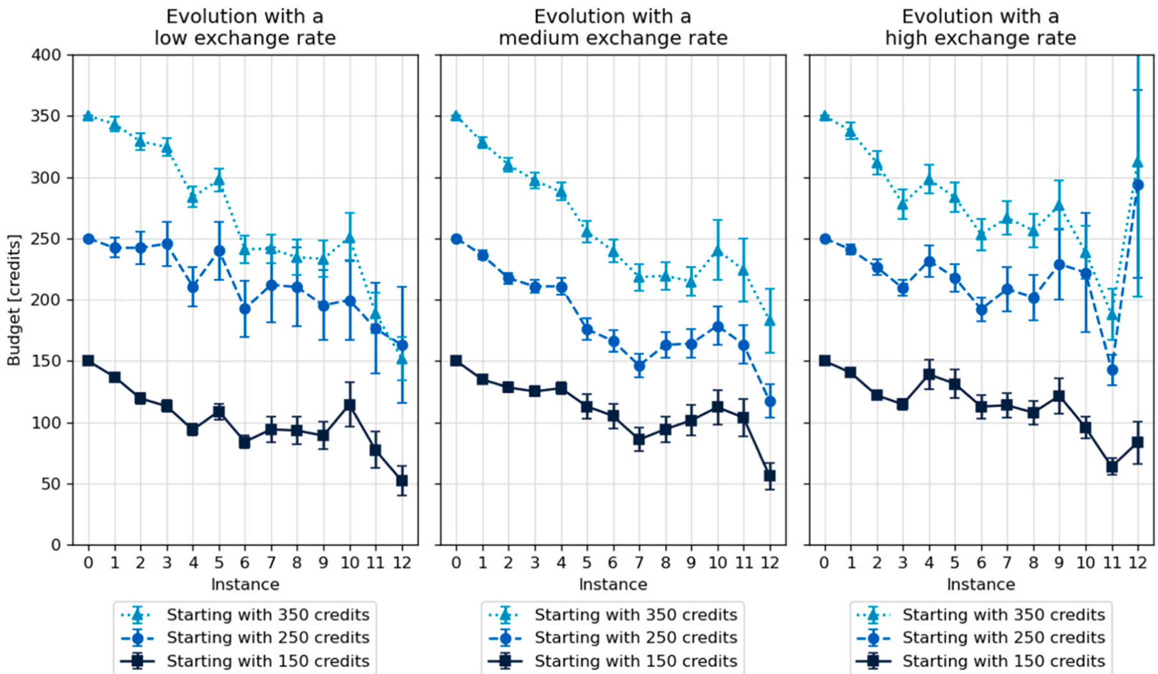


**Fig. 9.** Credit balance evolution for each of the nine block combination subsamples.

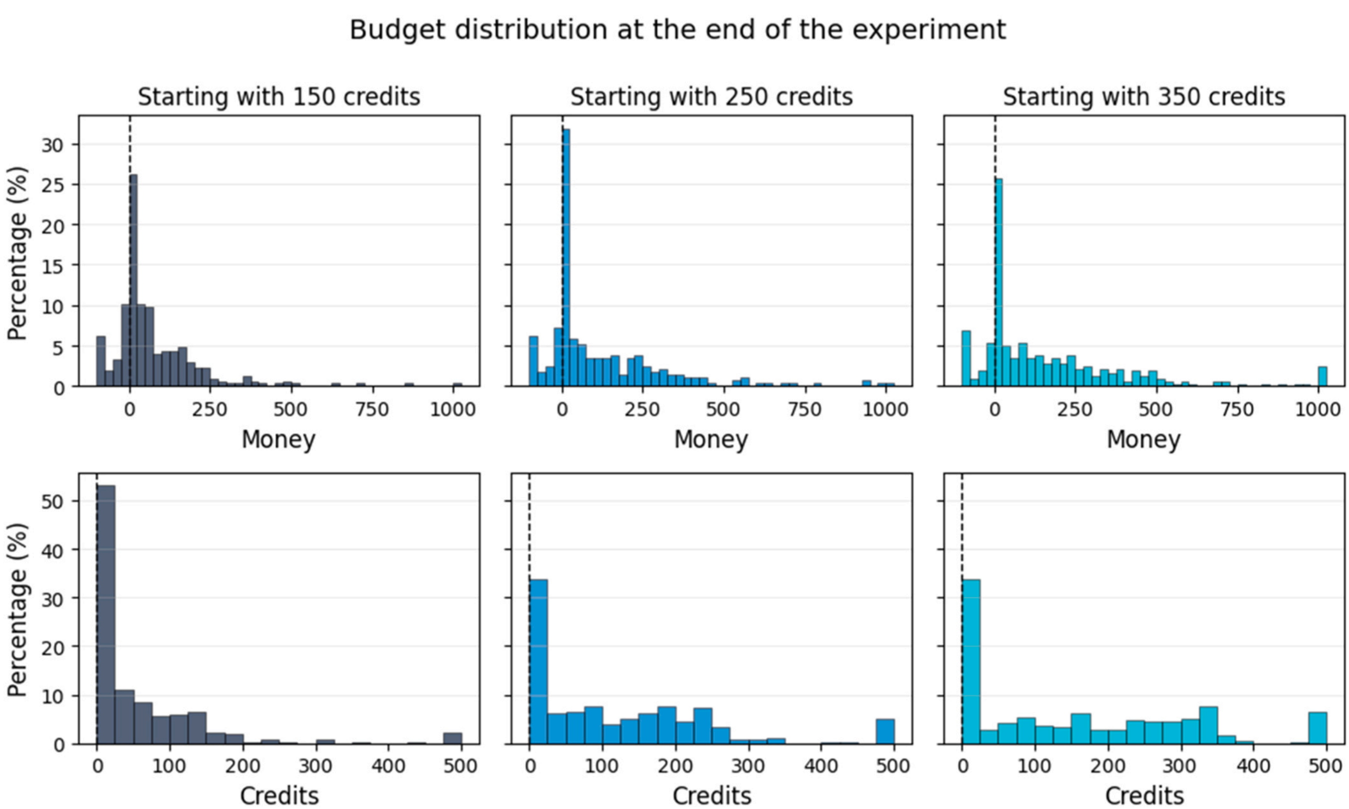


**Fig. 10.** Distribution of credits and money at the end of the experiment.

any value above 10 can be assumed to represent such a decision rule (Van Cranenburgh et al., 2015). To simplify the subsequent model estimations, we continue with a traditional RUM-MNL model formulation. Multiple MNL model formulations are thus tested, the results of which are reported in Table 16 in Appendix C. Parameter estimates that are significant ($p < 0.05$) were all found to have logical and expected signs. From the outcomes, we reaffirm that TMC costs are perceived directly and not converted into monetary values (€) based on the exchange rate. To clarify, that means that for a trip that would cost 50TMC, respondents would consider that cost directly, rather than for example converting it into €40 based on a 0.8 €/TMC exchange rate. A variety of different exchange-rate perceptions were tested for this (current exchange rate,

**Table 5**
Overview of average leftover credits and bank balance at the end of the experiment.

| Starting budget group | Average leftover credits | Average bank balance | Number (share) ending in money deficit |
|---|---|---|---|
| **150 credits** | 57 credits | €65 | 66 (21.6 %) |
| **250 credits** | 93 credits | €193 | 51 (17.5 %) |
| **350 credits** | 142 credits | €216 | 48 (15.0 %) |

average of past few exchange rates, all exchange rates) and all models resulted in an inferior model fit compared to a simple formulation which includes a direct TMC perception coefficient.

Next, we assess the impact of exchange rate on the perception of credits and also conclude that it does in no way affect the perception of TMC. This is based on the idea that if TMC are cheaper to buy, they may be perceived less negatively, meaning respondents would be willing to pay more for travel time improvements and vice versa. We specify the exchange rate perception both directly and as the difference between current and the average of previously experienced rates.

Our findings suggest that what does impact the perception of TMC is the balance in respondents fictional account, i.e. the number of TMC they had at their disposal affects how much they value them: the more they had, the more they were willing to spend and vice-versa. In other words, the abundance or scarcity of the TMC as a separate distinctive resource (different from money) determines the value attached to it. The best model fit is achieved when we consider the balance after any potential credit trading and transforming the balance by means of natural logarithm. Balance after trading achieves a higher model fit compared to before the trade as this is the amount respondents seem to consider when making their travel choice, whereas before the trade, the balance was less influential as it could have still increased or decreased due to a potential trade. A natural logarithm transformation is used to test the assumption that the marginal value of a single TMC decreases with an increasing total balance.

Additional balance-related specifications are also tested, such as the share of the initial balance remaining and its natural logarithm transformation, as well as dummy variables corresponding to the starting budget block etc., but none resulted in a model fit as high as the previously mentioned model.

Finally, we also test how trading actions influence TMC perception. This achieves the best model fit of all, both on its own and when paired with the natural logarithm transformation of the balance. As expected, respondents were willing to spend more TMC after just having bought some, whereas selling them made them less willing to spend.

### *5.2. Latent class choice models*

To obtain additional insights and to better understand how perception differs within the population, a series of latent class models are also estimated. Given the results from the estimated MNL models, a specification including the current TMC balance is employed. We do not add the specification with two dummy variables on buying/selling behaviour, since those are more context specific and not easily translatable to other scenarios.

Starting with the number of classes, we select a 4-class model as the optimal. The BIC indicator would suggest a model with more classes (even seven still showed significant improvements), however for models with five or more classes, one class is very small (~1 %), violating one of our criteria for defining the optimal class number. The final 4-class model, including model fit, taste parameters and class membership parameters, is reported in Table 6.

Next, we describe each of the four classes, discussing their travel behaviour characteristics and personal circumstances. Travel behaviour is assessed by analysing their respective WtP for travel time improvements (shown in Fig. 11), modal preferences and the associated trade-offs with travel time (Table 8) and cost (Fig. 12) and how the current

**Table 6**
Model outcomes of the final model.

| **Model fit** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Parameters** | 56 | | | | | | | |
| **Null LL** | -12,089 | | | | | | | |
| **Final LL** | -6270 | | | | | | | |
| **Rho-square** | 0.4813 | | | | | | | |
| **BIC** | 13,062 | | | | | | | |
| **Taste parameters** | | | | | | | | |
| | **Class 1** *Cyclist* | | **Class 2** *Multimodal Travellers* | | **Class 3** *Car drivers* | | **Class 4** *Public transport users* | |
| Class size | 35 % | | 34 % | | 19 % | | 12 % | |
| | Est | t-val | Est | t-val | Est | t-val | Est | t-val |
| *Constants* | | | | | | | | |
| PT | -3.770 | -12.40 ** | -0.351 | -1.24 | -0.116 | -0.78 | 2.000 | 4.78 ** |
| Car | -3.870 | -5.97 ** | -0.383 | -1.08 | 0.648 | 2.96 ** | -0.501 | -1.00 |
| *Common parameters* | | | | | | | | |
| Travel time | -0.079 | -2.55 ** | -0.145 | -9.61 ** | -0.034 | -2.50 ** | -0.039 | -3.30 ** |
| TMC | -0.111 | -3.44 ** | -0.150 | -5.77 ** | -0.085 | -5.57 ** | -0.019 | -0.22 |
| Balance-TMC interaction | 0.017 | 3.61 ** | 0.017 | 4.39 ** | 0.013 | 4.92 ** | 0.000 | 0.00 |
| **Class membership parameters** | | | | | | | | |
| Constant | *Baseline* | | -0.627 | -1.15 | 0.775 | 1.46 | -1.140 | -1.52 |
| Female | | | 0.547 | 2.40 ** | 0.489 | 1.84 * | 0.617 | 2.03 ** |
| Age 50–64 | | | -0.672 | -2.76 ** | -0.529 | -1.73 * | 0.224 | 0.60 |
| Age 65 + | | | -0.124 | -0.35 | 0.311 | 0.91 | 0.997 | 2.59 ** |
| Middle educated | | | -0.186 | -0.48 | -0.862 | -2.39 ** | -0.987 | -2.09 ** |
| High educated | | | 0.087 | 0.20 | -1.330 | -3.57 ** | -0.927 | -2.00 ** |
| 0 car household | | | 0.579 | 1.91 * | -1.090 | -2.47 ** | 0.658 | 1.46 |
| Bike weekly | | | -1.410 | -4.11 ** | -2.390 | -8.02 ** | -3.520 | -8.03 ** |
| BTM[a] weekly | | | 2.250 | 5.76** | 0.944 | 2.35 ** | 3.210 | 6.84 ** |
| BTM[a] bi-monthly | | | 1.220 | 3.35 ** | 0.434 | 1.52 | 0.755 | 1.67 * |
| Car weekly | | | 1.360 | 4.86 ** | 1.410 | 3.73 ** | 1.510 | 3.45 ** |
| Finance Item 4 | | | -0.265 | -2.36 ** | 0.001 | 1.91 * | -0.177 | -1.12 |

** $p \leq 0.05$, ** $p \leq 0.1$
[a] Bus, tram and metro

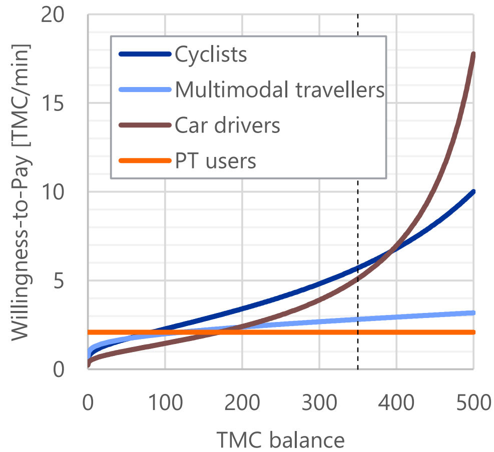


**Fig. 11.** Willingness-to-Pay for travel time improvements, given the TMC balance.

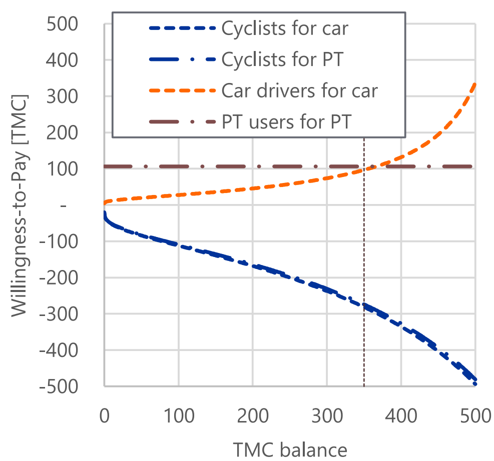


**Fig. 12.** Willingness-to-Pay for modes with respect to the bicycle, given the TMC balance. (only significant modal preferences are shown).

balance affects the perception of TMC cost (Table 7). The latter specifically looks into the tipping point of the TMC balance; as the perception of TMC is affected by the current balance, this table shows at what point does the cost of travelling become irrelevant, i.e. respondents have enough in their TMC wallet to not have to worry about the cost. The personal characteristics are analysed through the respondents' use of travel modes on a weekly basis (Fig. 13 and Fig. 14) and by means of comparing the socio-demographic characteristics between individual classes and the sample, as shown in Table 9. To ease the interpretation, each of the classes is given a name highlighting one of its key behavioural characteristics. The four classes, including their size within the sample are:

- Cyclists (35 %)
- Multimodal travellers (34 %)

**Table 7**
Balance value where travel price becomes irrelevant for the decision-maker (given the natural logarithm transformation of how TMC balance affects the perception of TMC costs).

| | |
|---|---|
| Cyclists | 802 |
| Multimodal travellers | 7544 |
| Car drivers | 577 |
| Public transport users | n/a |

- Car drivers (19 %)
- Public transport users (12 %)

### 5.2.1. *Class 1: Cyclists*

The first and biggest class within the sample, with ~35 % of all respondents, are the cyclists. This is due to their strong preference for the bicycle both in the SP experiment as well as in everyday life. In the experiment, members of this class find travelling by car or PT to be more attractive than the bicycle when the travel is half an hour faster by either of the two modes, while still being priced equally (Table 8). They are among the more time-sensitive classes, showing the highest WtP for travel time improvements (for TMC balance values between 100 and 400, see Fig. 11). The latter also indicates quite strong sensitivity to their current TMC balance (2nd most sensitive of all four).

Members of this class are somewhat more likely to be male and middle-aged (50–65 years old), whereas other socio-demographic criteria broadly align with the sample averages. Stronger patterns can be observed when considering their travel behaviour (Fig. 13 and Fig. 14); almost 90 % of the members in this cluster cycle on a weekly basis, sometimes in combination with PT or the car, with the latter being more likely than the former. This also aligns with their slightly below average car ownership of 0.86 per household, compared to the 0.92 sample average.

### 5.2.2. *Class 2: Multimodal travellers*

The second largest class, with an almost equal share (34 %), are the multimodal travellers. Unlike the previous class, they have no noteworthy modal preferences, with both mode-specific constants being insignificant ($p > 0.25$). They are more likely to be cost-sensitive, with their TMC balance having a limited impact on their WtP (Fig. 11, Table 7).

Consistent with their stated behaviour, the individuals within this class tend to be fairly multimodal in their day-to-day life, with almost 2/3 using at least two modes on a weekly basis (Fig. 13). They are the second most frequent users of the car, bicycle and BTM (bus, tram and metro), as well as the most frequent train users (Fig. 14). Looking at their socio-demographics, they are the youngest class, more likely to be female and attained the highest level of education, with 65 % having a university degree, compared to 55 % in the sample. They also have an above average share of employed individuals (Table 9).

### 5.2.3. *Class 3: Car drivers*

Car drivers are the third largest class at ~19 %. As the name suggests, members of this class prefer to travel by car, albeit their cost sensitivity can also persuade them otherwise. Depending on their TMC balance, they are likely not willing to spend more than 100TMC for the car over the bicycle or PT (given the same travel time). Curiously, while they are very cost sensitive at lower balance levels, if they have more than 200, and especially if they have more than 400 in their TMC wallet, they are willing to spend a lot on both travel time improvement as well as to travel by car. Given the natural logarithm transformation of the impact of TMC, the cost would become irrelevant for car drivers at a TMC balance of 577 (Table 7). That means that in their case, the number of credits they are allocated is highly influential.

Considering their socio-demographics, they have the highest car ownership of any class, at 1.17 per household, with only 7 % not having a car, whereas the sample average is 26 %. This high ownership also translates into the highest car use of any class, with some 75 % using it weekly. On average, they have the lowest level of completed education, with only 39 % having a university degree (sample average 55 %). They also tend to be older and thus more likely to be retired rather than still working or studying. They are also more likely to be living with others, like their partner, but with no children in their household.

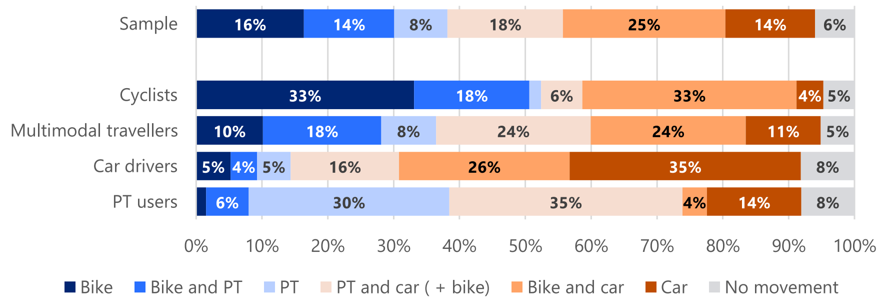


**Fig. 13.** Average weekly travel pattern of the different clusters and full sample (shared of <3 % are not indicated).

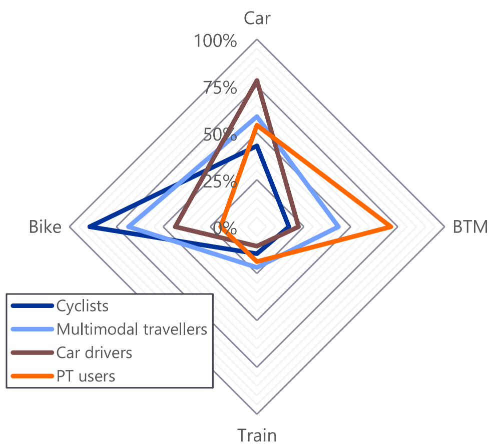


**Fig. 14.** Weekly use of modes by the different clusters.

**Table 8**
Trade-off values between modal preferences and travel time (shaded italic values indicate insignificant parameters).

| | PT [min] | Car [min] |
|---|---|---|
| Cyclists | -33 | -34 |
| Multimodal travellers | *-2* | *-3* |
| Car drivers | -2 | 7 |
| Public transport users | 106 | *-25* |

*5.2.4. Class 4: Public transport users*

The final and smallest class consists of PT users, with only 12 % of the sample. As the name suggests, members of this class have a strong preference for PT. They also have a fairly high cost sensitivity and low time sensitivity. Interestingly, they are the only group who's perception of TMC does not seem to be affected by their current TMC balance, willing to spend the same irrespective of how much they have. This means that with lower balances, they seem to be the most time-sensitive, becoming the most cost-sensitive when the balance exceeds 150TMC.

Among the four classes, they are the oldest and thus most likely to be retired (28 %, compared to 17 % sample average). Similar to the car drivers, they are less likely to have a university degree and also have the lowest income of any class. Contrary to the previous class however, they have the lowest car ownership of any class (0.77 cars per household, with 37 % having no car) and are also most likely to be live in a single-person household.

## 6. Trading behaviour

Having analysed the mode choice part of the experiment, we now turn to the trading behaviour. This is done through a series of specifications of multiple linear regression models. We start by determining what the best specification for the dependent variable is, namely the number of credits traded. As mentioned in the Section 3, we test five options, the results of which can be seen in Table 10. The natural logarithm transformation seems to be the best performing, followed by the truncated options, with lower truncation values resulting in higher model fits. These outcomes are likely caused by a large number of no-trading instances (58 % in total) and a few extreme outliers, when individuals traded several hundreds of credits.

Since our dataset contains a substantial number of zeros, we also test a hurdle model: we first estimate a discrete choice model where the options are "buy", "sell" or "not trade". For those choosing a trade action, a regression model is estimated to understand how many credits they would trade. The choice model resulted in a rho-squared of 0.16 and the regression model using only trading actions achieved an $R^2$ value of 0.253.

Wishing to account for both the non-trading actions and extreme trading values in a single model specification, we continue with the multiple linear regression, using the natural logarithm specification. We also see from Section 5 that a natural logarithm transformation seems to be appropriate to account for the perception of TMC. In this case, the perceptual difference between buying 20 or 30 credits seems to be higher than between buying 200 or 210 credits.

Next, we test different specifications for two key aspects of the survey, namely the exchange rate and the credit balance. We test all 12 combinations of both specifications with the $R^2$ model fit presented in Table 11. For credit balance, a natural logarithm transformation again proves to achieve the best model fit (in all three combinations of exchange rate specifications). Similarly, the Δ rate specification performs best in all four combinations with credit balance. These results suggest that for exchange rate, respondents do keep past rates in mind and compare the average of what they experienced so far to what is in front of them in that instance. With respect to balance, respondents seem to have had a mental estimate of where they are in respect to where they 'should be', given their starting budget and the number of travel instances that are still ahead of them.

Having determined these, we include all socio-demographic and experiential variables into the model and sequentially remove insignificant parameters, until only significant ones remain. The final model achieves a model fit $R^2$ of 0.134 and a BIC value of 47,040.55. The parameter estimates are presented in Table 12.

The exchange rate and balance both affect behaviour in the expected way. If the exchange rate is lower than the average of past rates up till that point, respondents are more likely to buy and vice-versa. Similar for the credit balance, if respondents have fewer credits than can be expected to have by this point (assuming an even consumption), then they are also more likely to buy credits.

Next, we include a variable corresponding to how many trips still need to be made. Results suggest that people are likely to buy more credits if more trips are yet to be made. This can be seen as buying to save up for potentially more expensive trips in the future or to potentially sell later on if the exchange rate is attractive.

We include two dummy variables on the experience of buying and selling, reflecting if the respondent had in any of the past instances

**Table 9**
Socio-demographic characteristics of individual classes with respect to the full sample).

| | | Sample | Cyclists | Multimodal travellers | Car drivers | PT users |
|---|---|---|---|---|---|---|
| Gender | Female | 51% | 45% | 57% | 53% | 51% |
| | Male | 48% | 55% | 43% | 46% | 49% |
| Age | 18-34 | 26% | 22% | 35% | 22% | 18% |
| | 35-49 | 23% | 22% | 27% | 22% | 14% |
| | 50-64 | 32% | 40% | 24% | 29% | 34% |
| | 65+ | 19% | 16% | 14% | 26% | 34% |
| Education | Low | 12% | 10% | 7% | 21% | 19% |
| | Middle | 33% | 32% | 28% | 40% | 36% |
| | High | 55% | 58% | 65% | 39% | 44% |
| Income | < 30k | 22% | 22% | 21% | 21% | 25% |
| | 30k-50k | 28% | 27% | 28% | 29% | 29% |
| | 50k-100k | 27% | 29% | 27% | 25% | 22% |
| | > 100k | 9% | 9% | 10% | 7% | 6% |
| | n/a | 15% | 13% | 15% | 18% | 18% |
| Employment | Employed | 65% | 67% | 70% | 60% | 53% |
| | Retired | 17% | 15% | 12% | 22% | 28% |
| | Other | 18% | 18% | 18% | 18% | 18% |
| Household | Single | 31% | 32% | 33% | 24% | 36% |
| | With kids | 31% | 32% | 32% | 33% | 23% |
| | Without kids | 37% | 36% | 35% | 42% | 41% |
| | Car ownership | 0.92 | 0.86 | 0.89 | 1.17 | 0.77 |
| | Driving license | 82% | 82% | 83% | 90% | 72% |

***Green** indicates levels that are at least 5p.p. above the sample average*
***Red** indicates levels that are at least 5p.p. below the sample average*

**Table 10**
Model outcomes for different specifications of traded credits.

| Specification | $R^2$ |
|---|---|
| Linear | 0.012 |
| Truncated at +/-50 | 0.114 |
| Truncated at +/-100 | 0.096 |
| Truncated at +/-200 | 0.075 |
| Natural logarithm | 0.134 |

**Table 11**
Model fit outcomes of the different exchange rate and credit balance specifications.

| | | Credit balance | | | |
|---|---|---|---|---|---|
| | | Current | Expected | Δ balance | Δ ln (balance) |
| Exchange rate | Rate | 0.100 | 0.099 | 0.099 | 0.114 |
| | Average rate | 0.062 | 0.060 | 0.060 | 0.077 |
| | Δ rate | 0.119 | 0.118 | 0.118 | **0.133** |

bought or sold credits and therefore have an experience with it. They both show a strong relationship, with buying experience resulting in an increasing likelihood to buy more credits also in the future and the same for selling, albeit to a slightly smaller extent.

To account for the mode choice characteristics in the trade instance, dummy variables of mode choice and two for travel time and cost are

**Table 12**
Model estimates of the final regression model.

| | Estimate | t-val |
|---|---|---|
| Constant | -0.0217 | -0.248 |
| Δ rate | 0.6110 | 27.724 ** |
| Δ ln(balance) | 0.2490 | 14.534 ** |
| # trips remaining | 0.0428 | 6.128 ** |
| Buy experience | 0.7449 | 17.274 ** |
| Sell experience | -0.5820 | -13.121 ** |
| Chosen bicycle | -0.2384 | -3.715 ** |
| Chosen PT | -0.1013 | -2.529 * |
| Chosen car | 0.3180 | 2.304 * |
| Chosen time | -0.0087 | -3.655 ** |
| Chosen cost | 0.0067 | 2.056 * |
| Weekly bicycle | -0.1099 | -2.513 * |
| Weekly train | -0.1386 | -2.609 ** |
| F1 Risk-averse investor | 0.0574 | 2.683 ** |

** p ≤ 0.05, ** p ≤ 0.1

included in the final model. Respondents are more likely to sell credits if they chose to travel by bicycle or PT, while travelling by car is more likely to result in buying credits. Travelling by bicycle was always a cheap option in the experiment, meaning that respondent could likely sell their leftover credits. This, albeit to a lesser extent, also seems to hold for PT, whereas the inverse seems to be the case when travelling by car, which is quite expensive. High travel cost naturally results in a higher likelihood of buying credits while high travel time in selling, although this effect is found to be rather limited for both.

Finally, of the socio-demographic parameters, age, gender, education, income and working situation have all been removed in the process due to their insignificant contribution. Individuals who travel at least once on a weekly basis by bicycle or/and by train are more likely to sell credits. Given the results from Section 5 and the high correlation between mode choice and actual mode use, frequent cyclists are likely also those choosing to travel by bicycle in the experiment, meaning they are more likely to sell.

To assess the impact of financial literacy and the level of risk people are willing to take in financial investments, we also included attitudinal statements on the topic in the survey and perform an exploratory factor analysis. The full results can be seen in Appendix D with the final factor loadings shown in Table 17. We test the two obtained factors in the regression model and only Factor 1: Risk-averse investor seems to have an impact, making respondents more likely to buy. This suggests that more careful investors seem to prefer buying some additional credits, perhaps in order to have some safe buffer for future travel instances.

It is important to note what the impact of utilising a natural logarithm transformation is. As can be seen in Fig. 3, the natural logarithm function has a decreasing marginal value of each additional credit. However, when doing the inverse, as shown in Fig. 15, an exponential transformation is made. This means that in this analysis, each additional logarithmically transformed traded credit contributes proportionally more. Going from a value of 2 to a value of 3 means ~13 additional credits traded, but when going from 3 to 4, the increase corresponds to ~35 credits. From a behavioural perspective, this means that when the parameters are at odds with each other (some positive, some negative), i.e. if the exchange rate is favourable, but they have more credits than expected, their effects cancel each other out and hardly any credits are traded or more likely none at all. But if they align, i.e. good exchange rate and lower than expected balance, they have a synergetic effect resulting in a non-linear, exponential relation.

## 7. Discussion

To get a better understanding of how the design and assessment of a potential TMC scheme could benefit from the behavioural findings reported above, we discuss potential policies and their outcomes in the following subsection, as well as broader possibilities and implications of implementing a TMC-based transport policy in Section 7.2.

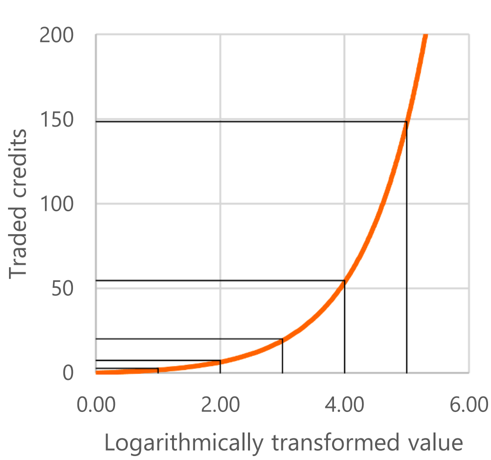


**Fig. 15.** Logarithmically transformed value of traded credits.

### 7.1. Policy examples

To simulate a hypothetical trip in an urban area, we use an example from Amsterdam, the characteristics of which are shown in Table 13. The TMC costs are set based on values from the survey.

Given the influence of the traveller's current credit balance, we start by assessing how travel behaviour changes with the number of credits in the traveller's wallet, the results of which are shown in Fig. 16. The full sample chart reveals that with more TMC in their account, people are more likely to travel by car and PT, whereas on a tight budget, they will choose the bicycle. While this is not surprising, it shows also that the rate of change primarily occurs with smaller balance levels. Once it exceeds 100TMC, the modal split mostly stabilises due to the logarithmic specification of credit balance.

Considering the different travellers' classes, they nicely show their namesake, especially the Cyclists and PT users, who almost exclusively choose their preferred mode. The PT users' insensitivity to current balance is also clearly evident from the flat modal split, whereas other classes show a variable split for different balance levels. Car drivers show greater variability in their behaviour, yet their high sensitivity to credit balance is evident from the increase in the share of car trips as their balance increases. It is also interesting to note that this happens almost exclusively at the expense of the bicycle, while the share of PT is almost constant at ~30 %. Finally, multimodal travellers seem to primarily travel by bicycle or PT in this particular instance, with the former being preferred roughly up until 70TMC, whereas the latter is preferred when the traveller has a higher credit balance. Although they do not have a strong dispreference for the car, its high price is what is keeping its modal split below 10 %.

Next, as the price of car travel varied substantially in the survey, and it is also likely to become the primary target of potential TMC-style policies, namely to reduce car use, we test how varying the price of a car trip on the same route (Table 13) affects the modal split. The results are shown in Fig. 17. Here, the opposite trend can be seen as compared to Fig. 16, which is to be expected. Car is much more preferred when it is cheap, achieving a market share of almost 30 % in the cheapest scenario. This then decreases sharply, dropping to only 18 % when the price equals that of PT (15TMC), below 10 % when it costs over 35TMC and below 5 % at ~60TMC. This demonstrates the large impact of TMC pricing on mode choice behaviour.

Looking closer at the classes, the cyclists and PT users are again essentially unimodal with their respective modes, with the car taking up $<$ 10 % of the modal split. Multimodal users also live up to their name, showing a roughly even split between the three modes when they are also roughly equally priced. The car then quickly loses ground, dropping below 10 % when the price exceeds 30TMC. Car drivers would primarily opt for the car, with over 50 % choosing it if it costs up to 10TMC. Although Car drivers have a high preference for the car, they are also very cost sensitive, meaning that the bicycle and PT both overtake the car when the price exceeds 40TMC.

From these analyses, we see that about half of all travellers, namely the Cyclists and PT users, making up a combined share of 47 %, are fairly insensitive. Even when testing for the price and travel time variability of the bicycle or PT, these two groups exhibit very limited changes in their behaviour, sticking to their namesake mode to a large extent ($>$75 %). While this may not be desired when implementing transport policies,

**Table 13**
Hypothetical trip characteristics.

| | Bicycle | Public transport | Car |
|---|---|---|---|
| Travel time [min] | 24 | 14 | 18 |
| Travel cost [TMC] | 1 | 15 | 40 |

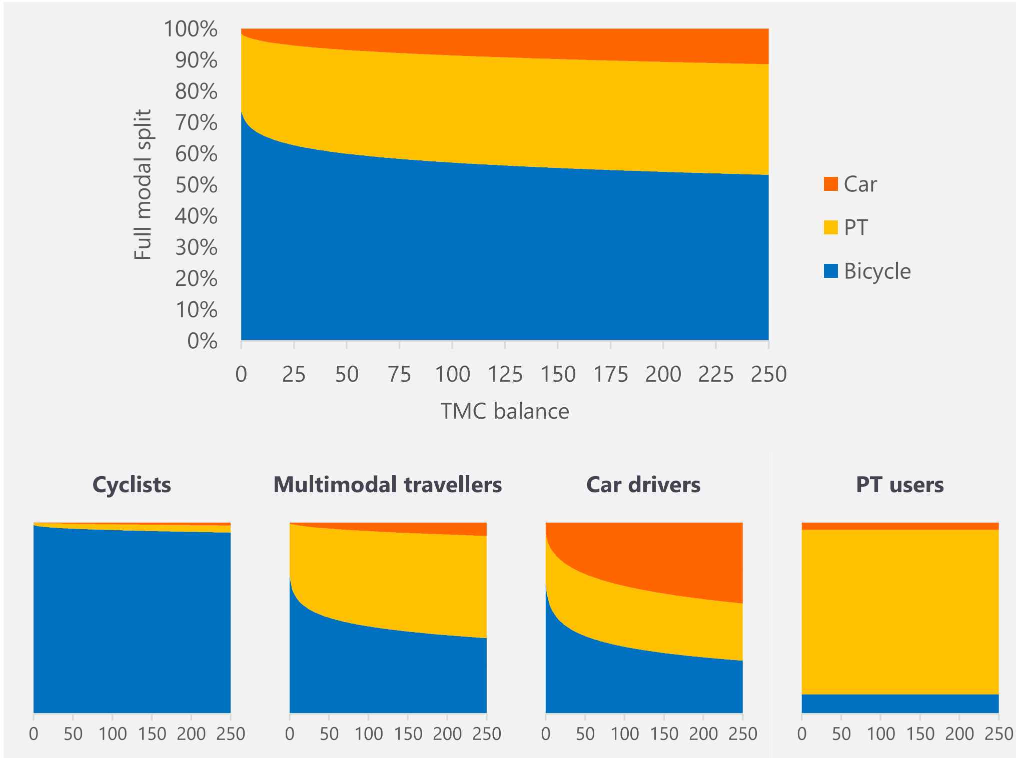


**Fig. 16.** Modal split given a variable TMC balance (for the full sample above and individual classes below).

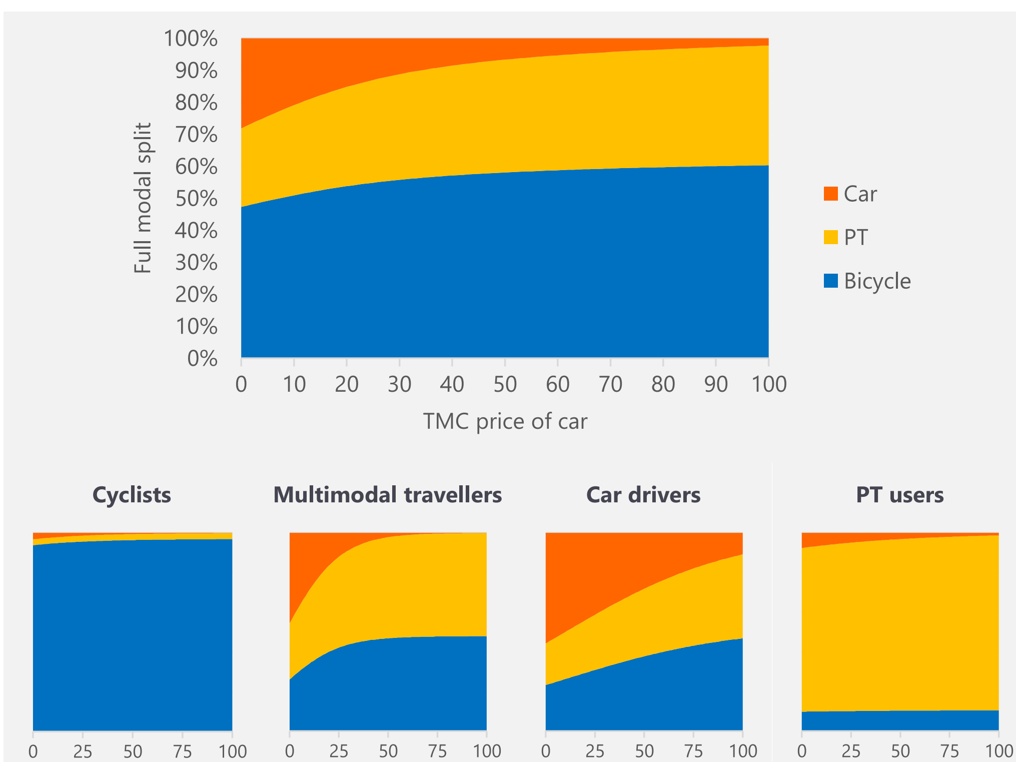


**Fig. 17.** Modal split given a variable cost for car (for the full sample above and individual classes below).

cycling and using PT tends to be preferable to driving and transport policies primarily do not try to reduce the use of these modes, making the insensitivity somewhat less problematic. Car use on the other hand seems to be fairly easily influenced, as seen in both sensitivity analyses carried out above.

### 7.2. Implementing a TMC scheme

To enrich our understanding of possible responses to the introduction of TMC, we conducted a public event devoted to this topic on the 23rd of April, 2024. There, 43 participants were acquainted with the concept of tradeable mobility credits and a live version of the SP experiment presented in Section 2 (with some adaptations) was carried out, a sort of a serious game. Thereafter, participants shared their thoughts, opinions or concerns about such a policy.

What came up most often, also through an open question at the end of the online survey, was that such a scheme would introduce a barrier for some travellers, as they would not only have to think about travel time and cost, but now keep an eye on the credit trading market, think when is a good time to buy or sell credits, and plan well enough ahead to make sure all trips can be carried out. This absence of good planning, according to some, would result in reduced spontaneity in social life due to stringent travel-related considerations.

Another point of debate was how the TMC should be distributed among residents. In the experiment and the serious game, all participants were awarded the same number of credits. This was immediately put into question with proposals for alternative mechanisms. This gives rise to additional questions on what is equitable and/or fair, who deserves more credits and why. This discussion boils down to individual traveller needs, which the participants themselves could not fully agree on what qualifies as needs.

Lastly, and perhaps most detrimental for a TMC policy, is the concern around privacy and being tracked. For such a policy to take place, certain behaviour monitoring would need to be implemented to confirm how people travel. While PT already includes this to some extent and reasonable solutions could be found for the car, the same cannot be said for cycling and other active modes, the tracking of which many participants found intrusive and unacceptable. Excluding these modes would be possible in a TMC policy which does not charge the use of these modes. Wider adoption of a TMC-like policy is likely still some way away, but the topics brought up by respondents in the survey and participants from the serious gaming event warrant further exploration.

## 8. Conclusion

Through this research, we extend the knowledge on the perception and travel behaviour under the premise of a Tradeable Mobility Credits (TMC) scheme. Our results show that travellers' behaviour can be affected through such a policy, incentivising certain modes while discouraging the use of others. We show that introducing credits as a demand management system does affect travel behaviour choices, mainly through the number of credits respondents have available as well as the exchange rate which prevail in the market at any given moment, both of which are found to determine the buying and selling decisions made by travellers.

Analysing travel behaviour under a TMC-scheme, our results show that travel cost is perceived in TMC and not converted into the money currency (euro in our case) when encountering travel cost in the form of credits with the credit exchange rate shown alongside (the value of a TMC). This may presumably reflect a cognitive shortcut undertaken by respondents to minimise cognitive burden by making cost calculations in TMC-units. Even though we can conclude from the trading models that the concept of TMC trading was understood, the direct TMC cost was not translated into travel cost. This likely also explains the relatively high willingness-to-pay obtained in our study, as if the connection between travel cost in TMC and euros was not that strong, the respondents may have indicated they would spend more than they otherwise would.

We carry out a segmentation analysis, namely a Latent Class Choice Model, to better understand how individual classes within the population would behave. Model findings show four distinct classes who's behaviour differs primarily based on their preferred mode of travel and less on their price sensitivity. Three out of the four classes, making up almost 90 % of the sample, show some form of cost-sensitivity based on their TMC balance at the decision moment. Specifically, all three classes exhibit what Dogterom et al. (2017) refer to as *Loss aversion*, which suggest that people may be less willing to spend TMC when they have fewer credits. This manifests itself through the balance-TMC interaction, showing that respondents in all three classes had a lower WtP if their balance was lower.

Interestingly, current travel behaviour is the most significant predictor of future behaviour, whereas socio-demographic and attitudinal characteristics have a lesser impact. Two classes, making up 35 % and 12 % of the sample, respectively, show very limited sensitivity to travel time or travel cost, choosing to travel with their preferred mode in the vast majority of instances, the modes being the bicycle and PT, respectively. The public transport group also seems to be insensitive to their credit balance, meaning they are equally willing to spend a certain number of credits if they have many or few on their account. Two other classes showed more variability in their behaviour, namely the multimodal travellers (34 %) and car drivers (19 %). The former, as the name implies, had no strong modal preference and would use whatever has the best cost to benefit ratio. In the simulated scenarios, they tended to not travel much by car due to its high cost. The car drivers on the other hand, while strongly preferring the car, are also quite cost sensitive, meaning a high cost for car turns them away from it. Since these are primarily the groups for which we would like to see behavioural change in response to a TMC policy, these results are reassuring.

Credit trading behaviour on the other hand achieved on the whole lower model fits. Arguably, this can be partly attributed to the novelty of the concept and respondent's unfamiliarity with how such a system functions. A promising 40 % of all trading opportunities resulted in trading actions and over 80 % of respondents traded credits at least once during the experiment. Modelling and predicting the trading decisions made proved to be not straightforward. This is partly caused by many no-trading instances and some outliers, where respondents traded hundreds and thousands of credits. By mitigating both, we observe, as expected, that a lower than average exchange rate was a key motivator to buy credits and vice-versa for selling credits. Results also show that respondents considered their current balance in comparison to where it roughly should have been at a specific moment (considering how many trips still need to be made) when making buying or selling decisions. As could be expected, experience of having bought or sold before also has a strong impact. Perhaps more interestingly, socio-demographic characteristics did not have a significant impact on trading, with financial attitudes also having a limited effect.

From the two models, mode choice and trading, we see that there is some relation between the two, primarily through credit balance, yet the effect is not substantial. Only around half of the respondents exhibited sensitivity to cost, time or balance in their travel behaviour choices. While not ideal from a behavioural adaptation potential standpoint, half of travellers reacting to policy changes can still lead to substantial shifts in behaviour. Perhaps more interestingly, pricing itself has as high of an impact, if not higher, as TMC balance. This is an important insight for policymakers, as a TMC scheme may be much more difficult to implement, compared to more traditional pricing measures.

Analysing further the willingness-to-pay, the respondents exhibited fairly high WtP values with average values of 0.21€/TMC and 2TMC/min resulting in a WtP of 25€/h. These values are high when compared to average Dutch values of around 10–15€/h (Kouwenhoven et al., 2023), yet comparable to other studies in the field. Álvarez-Ossorio Martínez et al. (2025) for example, report WtP in the range of 30–40 €/h for a sample from Munich, Germany. These higher values are partly due to the hypothetical nature of an SP experiment, where respondents are not directly faced with the consequences of their actions. Alternatively, it could be related to the fact that travel costs seemed to have been perceived directly through TMC and not through money. This suggests that respondents were not directly transforming travel cost into money, meaning the relationship between TMC and money might have been weaker.

That being said, our study shows TMC schemes can produce the desired outcomes and their numerous benefits necessitate further research, to continue to improve our understanding of how such a system would function, the impacts of alternative design choices, and what are the major barriers and concerns of individuals in using such a system. Firstly, by engaging with a sample of travellers, researchers should get more insights into how they see themselves and their daily lives change were a TMC policy implemented, as well as what are potential issues in the current system that TMC could address, thereby making informed design choices. Secondly, given the wide variety of approaches to implementing TMC (Provoost et al., 2023), testing out how travel behaviour is affected under different circumstances is essential. Finally, it would be valuable to use these behavioural insights, to simulate how the impact of individual responses to a TMC policy result in collective impacts at the level of a city, region or even an entire country.

## CRediT authorship contribution statement

**Nejc Geržinič:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Oded Cats:** Writing – review & editing, Supervision, Project administration, Investigation, 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

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## Appendices

Appendix: Choice experiment design

Orthogonal design of the mode choice experiment from the survey.

**Table 14**
Orthogonal design of the mode choice experiment

| Choice set | Bicycle | | Public transport | | Car | |
|---|---|---|---|---|---|---|
| | Travel time | Travel cost | Travel time | Travel cost | Travel time | Travel cost |
| 1 | 20 | 3 | 10 | 15 | 10 | 60 |
| 2 | 30 | 1 | 30 | 15 | 10 | 60 |
| 3 | 10 | 2 | 10 | 5 | 20 | 80 |
| 4 | 10 | 1 | 20 | 25 | 30 | 60 |
| 5 | 10 | 2 | 30 | 25 | 20 | 80 |
| 6 | 30 | 2 | 30 | 5 | 20 | 80 |
| 7 | 20 | 3 | 30 | 15 | 30 | 40 |
| 8 | 20 | 3 | 20 | 25 | 10 | 40 |
| 9 | 30 | 1 | 10 | 15 | 30 | 40 |
| 10 | 10 | 1 | 20 | 5 | 10 | 40 |
| 11 | 30 | 2 | 10 | 25 | 20 | 80 |
| 12 | 20 | 3 | 20 | 5 | 30 | 60 |

Appendix: Calculating starting budgets

To determine the starting budgets, we use the target modal split for the current, intermediate and 2030 situations. Next, we determine how many credits would need to be spent to make all 12 trips with each mode. That means summing all the costs of each mode from Table 14. Next, we multiply the modal splits of each mode with the total costs of using them, then sum those products. The resulting values can be seen in the second-to-last row of Table 15. These values are then rounded to equidistant starting budget values.

**Table 15**
Calculation of starting TMC budgets

| | | Modal split scenarios | | |
|---|---|---|---|---|
| | Total credits | Current | Intermediate | 2030 Target |
| Bicycle | 24 | 33 % | 38 % | 44 % |
| Public transport | 180 | 27 % | 36 % | 45 % |
| Car | 720 | 40 % | 26 % | 11 % |
| Sum-product per Modal split scenario | | 346 | 259 | 173 |
| Rounded value | | 350 | 250 | 150 |

Appendix: Model outcomes of MNL models

**Table 16**
MNL model outcomes

| Group | Model | Param. | Model fit | Rho-sq. | BIC |
|---|---|---|---|---|---|
| | **Baseline** | **4** | **-8675.56** | **0.2824** | **17,388** |
| TMC conversion based on exchange rate | Current exchange rate | 4 | -8715.45 | 0.2791 | 17,468 |
| | Past exchange rate | 4 | -8715.45 | 0.2791 | 17,468 |
| | Past 2 exchange rates | 4 | -8716.15 | 0.2790 | 17,470 |
| | Past 3 exchange rates | 4 | -8717.48 | 0.2789 | 17,472 |
| | Past 5 exchange rates | 4 | -8718.45 | 0.2788 | 17,474 |
| | Past 10 exchange rates | 4 | -8718.96 | 0.2788 | 17,475 |
| Exchange rate impact on TMC perception | Current exchange rate | 5 | -8675.17 | 0.2824 | 17,397 |
| | Dif. from previous | 5 | -8674.04 | 0.2828 | 17,395 |
| TMC balance impact on TMC perception | Balance before trade | 5 | -8652.88 | 0.2842 | 17,352 |
| | Balance after trade | 5 | -8648.51 | 0.2846 | 17,344 |
| | % of initial balance | 5 | -8652.82 | 0.2842 | 17,352 |
| | LN (balance before trade) | 5 | -8675.54 | 0.2824 | 17,398 |
| | LN (after trade trade) | 5 | -8633.57 | 0.2858 | 17,314 |
| | LN (% of initial balance) | 5 | -8653.31 | 0.2842 | 17,353 |
| | 2x starting block dummy | 6 | -8642.41 | 0.2851 | 17,341 |
| Impact of trade on TMC perception | Buy & Sell dummy | 6 | -8561.70 | 0.2918 | 17,179 |
| | Linear trade amount | 5 | -8670.48 | 0.2828 | 17,387 |

Appendix: Exploratory factor analysis

We perform an exploratory factor analysis (EFA) on the 12 attitudinal statements related to financial literacy and investment risk. We apply the maximum likelihood method to extract the factors and the oblimin factor rotation (Schreiber, 2021). We then iteratively remove items that have a loading below 0.3 (Field, 2013), have a communality that is below 0.2 (Child, 2006) or a cross-loading that is either above 0.4 (Taherdoost, 2016) or more than 75 % of the main factor loading (Samuels, 2017). Through this approach, five of the 12 items are successively removed. The final outcome is shown in Table 17, with two factors and seven items in total. Based on the items and how they load onto the factors, we label them as:

- Factor 1: Risk-averse investors
- Factor 2: Stress-free investors

**Table 17**
Final pattern matrix of the EFA

| | | Factor 1 | Factor 2 |
|---|---|---|---|
| I2 | I do not like buying stocks simply because of the risks involved. | 0.834 | |
| I3 | I prefer investments that do not involve risks | 0.710 | |
| I5 | I always view risks as losing money | 0.556 | |
| I6 | I prefer safety to risk in financial investment | 0.740 | |
| I7 | I understand risk may be good, but I consider it as negative | 0.582 | |
| I11 | I am usually stressed about making a big daily financial investment decision | | -0.862 |
| I12 | Financial investment in general is very stressful to me | | -0.807 |

## Data availability

The data that has been used is confidential.

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