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Endowment Effect in Light Electric Vehicles Use: Experimental Assessment

Master's thesis

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I have written this Research paper/Bachelor Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Abstract

This paper investigates in a natural field experimental setting whether adding an endowment effect results in the transition from intention towards behaviour in the context of Micromobility Sharing Economy. We exploit the market of collective use of light electric vehicles (e-scooters and e-bikes) to investigate how the users who only downloaded a light electric vehicles application but have never used the service respond to additional endowment – whether it will nudge them to use the service and to exhibit loyalty to service provider in the form of subsequent rides. To do that, we conduct a natural field experiment with 400 users of sharing e-scooter service in Estonia and Latvia. The experiment revealed that providing an additional voucher as an endowment increased the odds of participants transitioning from intending to use the service to actually using it, compared to the control group who received no endowment. Furthermore, the results suggest that the endowment induced more loyalty to the service provider, as the treatment group had a higher probability of taking an additional ride than those who did not receive the endowment.

Keywords: endowment effect, Light Electric Vehicles (LEV), behavioural economics, natural field experiment.

JEL codes: C93. D91, P46

CERT code: S180.

1. Introduction

Shared micromobility refers to the collective use of a bicycle, scooter, or another light electric vehicle (LEV) that provides an on-demand and low-emission carbon footprint for short-distance travel (Parkes et al., 2013). These vehicles are rented for short periods of time. Usually, they are equipped with technology based on the Internet of Things (IoT) to benefit from the capacity to connect devices to the cloud and gather information from different sensors already included (Shaheen & Cohen, 2019). Breivold and Rizvanovic (2018) consider that this capacity of gathering data has helped firms to adapt and incorporate new business models and also has enabled the appearance of new companies.

Nowadays, to access the service of a shared e-scooter or e-bike, users need to download an application, create a profile with personal information, and add a method of electronic payment; without that, they cannot use the LEV.

There have been investments into shared mobility since 2010 for more than $100 billion US dollars, driven mainly by new technology such as smartphones and GPS, cities emission-cutting goals, or restrictions on private-vehicle use (Heineke et al., 2023). Those factors have led to many companies offering e-scooter and e-bike sharing services, even within the same city, which has sparked price competition and increased the size of their fleets in an effort to attract more users (Aarhaug et al., 2023).

In Germany, there are more than 62,000 e-scooters people can use, half of those located only in four cities (Gebhardt et al., 2021); to gain market share and cultivate customer loyalty in oversaturated and highly competitive markets, firms are increasingly recognizing the importance of delivering a distinctive customer experience to understand consumer preferences better and make data-driven decisions (Chang, 2018). By prioritizing differentiated customer-centric experiences, companies can effectively nurture strong customer relationships and drive consistent sales (Verhoef et al., 2009). The conclusion reached by Baumeister, et al. (2001) shows that to overcome one single bad experience, a person needs to experiment "far more" good experiences or events in their day and to establish that ratio, there is a need to understand what is good, bad and the strength of each of those events. Their research encompasses 15 different areas of study, some of which are receiving feedback, learning processes, human reaction to events, and emotion. The last two areas are critical for the digital era we live in. By recognizing that individuals respond differently to the same stimulus over time, firms can effectively influence emotions through various incentives. This understanding prompts a shift towards prioritizing emotional responses over purely rational ones, allowing companies to better connect with their target audience and foster deeper engagement (Modi, 2012).

Loewenstein, et al. (2001) focused on people's emotions and decision-making and how those strongly affect their perception of risk by relying on their previous experience or instinct rather than analytical decision-making processes. In addition, Zhu and Zhang's (2010) research on online customer reviews and their impact on sales states that online reviews in the digital era of social media have a strong correlation with potential sales firms may have. A study conducted by the United States analytics company, Qualtrics showed that 93% of consumers make decisions about consumption based on reviews they can find online, and 94% of adults between 18 and 34 consider those reviews as "personal recommendations" (2020).

In the shared micromobility sector, research about the user's experience has primarily focused on collecting information through surveys or questionnaires after using the service to identify the factors that influenced their decision to use a shared LEV (Elmashhara et al., 2022). However, it is essential also to consider the perspective of those who have installed the application or created a profile but have not yet used the service to gain a more comprehensive understanding of consumer behaviour, which is the focus of this paper.

This experimental research contributes to the literature by analysing those users who have only demonstrated intention of using the service, how they can transition towards showing actual behaviour, and the factors which can influence this transition. We define intention as the fact that a user completes all the processes towards using the service, except making the ride. Behaviour is deemed as an act that fulfils the intention as the users are riding the LEV. And loyalty is defined as subsequent (at least one) use of the service after the first ride.

I conduct a natural field experiment in collaboration with a scooter-sharing company in Estonia which benefits from the possibility of attracting new users and providing them with the experience of using their service. During this experiment, subjects are unaware they are being observed, and we can analyse their response after the beginning of it while benefiting from a realistic setting (Levitt & List, 2007). We will divide subjects into two groups: a treatment group receiving a five-Euro voucher as an endowment effect and a control group not receiving a voucher. The goal is to observe if the voucher affects users' transition from intention to behaviour and promotes loyalty. The benefit of an endowment effect in the form of "cash" is to help people to enter the market, as due to mental accounting, they are more comfortable about their finances because they may perceive the five euros as separate from their own capital or savings, reducing the risk of loss in case the experience is not satisfactory (Kahneman, 2011).

The experiment involves a group of randomly selected users who expressed an intention to use the service but had not yet utilized it between May 1st 2020 and June 1st, 2022. These users are then randomly assigned to either the treatment or control groups to investigate the impact of the endowment effect on their behaviour and loyalty, which they had not previously exhibited.

This paper is structured as follows: Section 2 presents a literature review and hypotheses. Section 3 outlines the experiment design and methodology. Section 4 discusses the experimental results and analysis of the regression models. Section 5 exposes our conclusions and recommendations.

2. Literature review and hypotheses.

The emergence of shared micromobility services can be traced to the growing demand for affordable, sustainable, and convenient transportation options for short-distance trips in urban areas (Shaheen et al., 2016). It has been driven by the surface of dockless e-scooters and e-bikes as those do not require additional infrastructure to return the vehicle to specific locations within the city and rely instead on the vehicle's GPS and users' smartphones (Gu et al., 2019). Users are choosing shared micro-mobility as a transportation option due to its affordability, ease of access, and convenient electronic payment methods. Additionally, it can be used for various purposes, such as leisure, exercise, and short trips, without the need for additional cash or user cards (Orvin & Fatmi, 2021). As these vehicles are powered by electricity and not by combustion engines, it also significantly impacts reduced emissions and congestion (Tran et al., 2015). Some additional factors that can motivate people to choose this way of transportation are bike lanes, availability of public transport, retail shops, and commerce (Faghih-Imani et al., 2014).

The shared micromobility also considers as a competitor the public transportation and other shared mobility services such as motorized vehicles (Saltykova et al., 2022). Its popularity has placed the services of shared LEV as a possible substitute of the traditional means of transportation (Yang et al., 2016), which has contributed to the fact that in some cities, it is possible to find several e-scooter companies operating in the same region and trying to differentiate by fleet size and price as presented by (Aarhaug et al., 2023).

In the case of shared e-scooters, the intention to use the service is influenced by price, the situation of the trip, and environmental factors (Lee et al., 2021). In a competitive market, firms often set their prices based on the preferences of the median consumer, a strategy known as the middle voter theorem. It means that offering a discount price can be an effective way to attract more customers, but as competitors may follow and adjust their prices accordingly, the effect of the discount is limited (Farm, 2017). Cheaper and similar rates across all the service providers' offers will limit the consumer's perspective, and there would be no new information that could lead to a revealed preference and consistently choosing one brand over the other (Samuelson, 1948).

Art Weinstein (2020) exposes the need for the brands to provide an experience to their users to be able to differentiate in the modern economy and not just the price or service, as a positive experience could lead to ignite reciprocity, higher profit, and recurrent revenue from their now regular customers (Johnen & Ng, 2022).

While much of the literature on shared LEVs focuses on the factors that motivate users to install apps on their personal smartphones to use the service and the strategies e-scooter providers implement to compete for market share and customer loyalty (Elmashhara et al., 2022; Guo & Zhang, 2021; Zhang et al., 2021), one area that has received comparatively little attention is the phenomenon of LEV users creating profiles and installing micromobility sharing apps but without ever actually using the service. In different business areas of e-commerce, this last behaviour is known and has been studied (Foroughi et al., 2023; Yildiz & Kitapci, 2018) as it allows firms to strategize to build a strong customer-centric brand to retain current users while at the same time trying to attract new clients, all this based on the feedback gathered from people who have used or acquired their service (Lemon & Verhoef, 2016).

Analogously, the strategy for the research presented in this paper builds on the contributions of Richard H. Thaler and Daniel Kahneman, specifically their work on the "Endowment Effect" (R. H. Thaler, 2016) and how it can be effectively leveraged to motivate users who have never experienced a particular service to engage with and utilize it. The endowment effect describes how people value items differently, whether in case they own them, compared to the value they assign to the same item but owned by somebody else. In other words, people often overvalue their possessions compared to their actual market value. Based on Thaler and Kahneman, we could consider different categories for endowment effect, such as ownership, monetary, social, or temporal endowment. The monetary endowment will be the chosen category for the research as it serves as a catalyst for another behavioural economic concept introduced by Thaler in his paper "Mental Accounting and Consumer Choice" (1985), known as mental accounting. The importance of it is that users can allocate the monetary endowment in a separate category from their savings or regular income while limiting the loss aversion effect in case of a non-satisfactory experience when using the e-scooter.

Richard Thaler explains the concept of value theory and loss aversion in the paper 'Toward a positive theory of consumer choice' published by the Journal of Economic Behaviour and Organization (1980). The concepts are simple; it grieves us more to lose a sum of money than the satisfaction associated with gaining the same amount, a definition also discussed by (Kahneman & Tversky, 1979). The loss felt from money or any other valuable object can feel worse than gaining that same thing, so losing disrupts people more than gaining.

In the globalized economy and as traditional economic theory explains, companies will maximize their profit subject to a budget constraint. Nevertheless, again (Kahneman et al., 1986) explore the concept of fairness and loyalty by highlighting how individuals value the idea of reciprocity. A firm will tend to maximize its long-term profits as long as they show "fair" behaviour towards its customers.

An increasing number of scooters in the streets of most major cities is pushing governments to regulate and adapt their roads to incorporate this reinvented mode of transportation. In the city of Tallinn, Estonia, you can find three different companies operating shared scooters as part of the micro-mobility industry (E. N. | ERR, 2020), and in the United States between the years 2010 and 2021, the National Association of City Transportation Officials reported 500 million trips made using micromobility services, ignited mostly by dockless e-scooters (NACTO, 2022).

As a result of the era of digital platforms and social media, customer experience has become relevant as a differentiator between firms to gain new customers and retain them (Bodaghi Khajeh Noubar &

Rostamzadeh, 2018). In the shared mobility industry, the experience provided during and after the ride can come only if people use the service (Khamissi & Pfleging, 2019). If customers do not actively utilize the service, they remain unexposed to it and cannot evaluate it and form their own opinion. Consequently, the online decision-making process heavily relies on reviews and the experiences shared by others, as they provide valuable insights and guidance for potential customers (Duan et al., 2008). In addition, (Cai et al., 2019) analysed the reviews of different riders after using a sharing bike service to understand what they call "residual effects," which demonstrated the strong correlation between how their own and other people's experiences of past behaviour influence the intention of using a bicycle sharing.

It seems that the importance of reviews and people's experiences affect what Kahneman and Thaler (2006) named "hedonic forecasting," which is the prediction of future decisions based on emotional states and is opposed to "decision utility," which is inferred traditionally from choices and used to explain those decisions. Therefore, under our definition of intention, which is a user that downloaded the application and created a profile but did not use the service, we will explore in this experiment two of the four hedonic forecasting states with the objective of transitioning customers towards the expected behaviour, which is getting them to use the service. According to , these two pillars are:

i. "When people forecast their future adjustment based on new life circumstances"
ii. "When choices are made on the basis of flawed evaluations of past experiences"

The endowment effect in the form of cash will provide subjects that have only demonstrated intention a "new life circumstance," something they did not have before and that does not expose a risk of losing their own money because of mental accounting. We aim to modify the circumstances and provide them with new information to test and evaluate the validity of the following hypothesis through empirical analysis:

Hypothesis 1. Adding an endowment effect will incentivize users to utilize the service (transition from intention to behaviour).

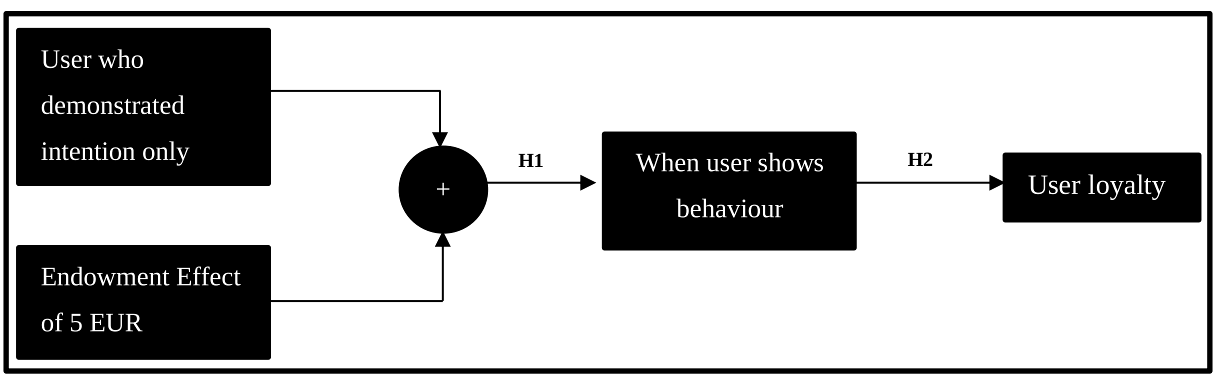
Provided that customers' satisfaction is an evaluation of a service based on their prior expectations and experience (Oliver, 1980), we can ascertain the presence of "loyalty" among users by assessing whether they exhibit a behaviour of continued engagement with the service, characterized by making at least one additional ride after their initial trial and leading to the second hypothesis tested by the experiment:

Hypothesis 2. The endowment effect will increase users' loyalty toward the service.

Figure 1 establishes a simple theoretical model and the two proposed hypotheses. We randomly selected people who only demonstrated intention. Afterward, we added an endowment in their favor to observe if they were motivated to demonstrate the behaviour of using the scooter and if they took at least one additional ride after their initial experience with the scooter. As part of the novelty of this research and to obtain accurate results and meaningful conclusions, we have chosen to conduct this study as a natural field experiment. The target population we are analysing consists of individuals who have never used the service before, even over extended periods of nearly two years. By adopting a natural field experiment approach, we can observe and assess the actual behaviour of participants without the involvement of a moderator or explicit explanation of the experiment. This setting allows us to obtain a realistic overview of whether the endowment facilitates the transition from intention to behaviour.

Figure 1.

Theoretical Model and Hypotheses.



3. Experimental design and methodology

To design a natural field experiment it is important to understand the environment in which it will be executed, the variable(s) to be measured and possible regulations as there should be almost no interaction with the subject allowing their desired preference emerge; opposed to an in-lab experiment in which users are aware they are being assessed (Carpenter et al., 2004; List, 2007). In our case, the initial step involves determining the best approach to contact the subjects while ensuring compliance with European privacy regulations, such as the GDPR. Key considerations include target and segmentation criteria, which ensure that information is only provided to users who are participants in the study. Additionally, participants are given the option to unsubscribe from the contact list at any time, allowing them to manage their involvement in the experiment.

The first option considered was utilizing the mobile application; however, its current set-up imposes limitations on reaching specific members or segments of the population. The second option involved sending text messages, but this approach poses the risk that subjects outside their country of coverage or without roaming service may not receive the notification. Lastly, the preferred and chosen option was to communicate with users via email. Email provides a personalized and easily accessible means of contact, regardless of the user's location, while also ensuring compliance with privacy regulations. More information about other methods considered can be found in Appendix A. To address potential confounders, specifically the factor of "language," thorough investigation of the subjects was conducted by taking into account three key factors. Firstly, the "preferred language" in which the application was installed by each subject. Secondly, the phone number country code was analysed to gather insights into the subject's country of residence. Lastly, the names and last names of the subjects were utilized to create message drafts tailored to their respective languages: Latvian, Estonian, and English. Appendix B provides the email drafts as references for each language. By incorporating these considerations, the study aims to ensure effective communication and mitigate the influence of language as a confounding variable in the experiment.

After determining the method to contact the users, the subsequent step involves defining the optimal approach to deliver the monetary endowment. The crucial aspect of an endowment is ensuring that it gives a sense of ownership, thus, to provide a five euro credit, a distinct and individualized code was generated for each participant in the treatment group. These codes were manually linked to their respective phone numbers and email addresses, and were set to expire after 30 days, rendering them non-transferable. This meticulous process guarantees the exclusivity and personalization of the endowment, reinforcing the notion that it truly belongs to each recipient and that loss aversion could be experienced if not used before the deadline.

To select experimental subjects, we relied on the raw data from users' database provided by the micromobility company who sponsored the experiment[1]. The raw data included information on members that have demonstrated intention to use the service, but not behaviour as of May 31st, 2022 (cut-off date).

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[1] The company preferred to remain anonymous within given research.

The total pool of potential subjects included 28,307 users (representing 31% of the total members registered in their database). Among these individuals, the duration of time that has elapsed since they installed the application but refrained from using the service exhibits a wide range, spanning from a minimum of 2 days to a maximum of 741 days. There were 19,430 (68.64%) subjects based in Estonia, 5,152 (18.20%) subjects in Latvia, and 3,725 (13.16%) subjects that reside in other countries but downloaded the application once they were in one of the two countries mentioned[2]. Raw data consists of phone number, account creation date, which helps to understand how long the user has been without making any rides, and in some cases, email address. It does not include other demographics such as age or gender.

In this experiment, we opted for email as the chosen method of contact, allowing us to engage with a total of 917 users who willingly provided their email addresses during profile creation and consented to receive marketing communication. Initially, due to budget constraints, the experiment was designed to include only 400 participants. To achieve this, we divided the experiment into two rounds, with each round comprising 200 subjects. Within each round, we randomly selected 100 subjects for the treatment group and 100 for the control group from the pool of users who had specified their email addresses. This random selection process ensured that the research findings could be generalized to the entire population, as it provided an equal opportunity for all users to be included, irrespective of their account creation date or country of residence, thus avoiding any potential biases.

After the random selection and allocation of users into their respective groups, the next step involves composing individualized emails for each participant. The content of the emails remains largely consistent, except for the inclusion of a personalized and untransferable code that can be redeemed within their application to avail a five euro voucher. It is important to note that the validity period of the endowment is restricted to 30 days. The first round, comprising 200 participants, took place in June 2022, followed by the observation period in July 2022. Subsequently, the second round commenced in July 2022 with another 200 participants randomly selected, and the observation period for this group occurred in August 2022.

In order to evaluate hypothesis 1 we define a "success" as a subject from either the treatment or control group, belonging to round 1 (or round 2), makes their first ride within the month of June (or July). In order to maintain consistency and ensure valid entries, rides made by users from round 1 (or round 2)

[2] Using the country code makes it possible to segregate the information into a new category named “country.” Estonia has country code 372 and Latvia 371; anything different will be categorized as “other.”

within July (or August) will not be considered. This deliberate time span of two months is intentional. We assume that the first month after receiving the relevant information for each group provides sufficient time for users to decide and complete their first ride. The subsequent second month allows ample time for subjects to exhibit a degree of loyalty, such as using the service at least once more. Table 1 provides a detailed breakdown of the distribution of individuals per round, per country.

Table 1.

Participants per round and presumed country of residence.

	Country	
Round	**Estonia**	**Latvia**
1	165	34
2	152	47

Throughout the course of the experiment, users received three individualized contact points: first, on the day of launch; second, midway through the experiment; and finally, three days prior to the end of the first month. The purpose of these contacts was to remind users about the benefits offered by the service. In addition, members of the treatment group were specifically informed about the expiration date of the endowment to ensure they could fully take advantage of it. Before the second and third contacts, the user database was updated to include only those who demonstrated intent. If a member from any group had already exhibited the desired behaviour, they were excluded from further email communications. The dynamics of the experiment are visually described in Figure 2.

To consistently collect experimental data, it is necessary to understand who made a ride. Filtering the information from the database allows us to get insights into the number of rides, the group the user belongs to, the total turnover, and the aggregate duration of all rides. At the end of each month, the data is updated, and it provides input for the model. To test the first hypothesis, we observe the subjects who did or did not make a ride and the group they belong to, their country, and round. To test the second hypothesis, we introduce a new binary variable called "extra_ride" which takes on a value of true if the subject took more than one ride during the two-month experimental period, and false if the user did not take any rides or only took one ride.

In practice, we cannot observe the user's utility concerning the endowment or fairness perception, but whether the event of making a ride happened or not. Formula 1 represents the relationship between explanatory and dependent variables

$$P\{y_i = 1|X_i^n\} = \alpha + \beta Treat_i + \gamma_n X_i^n + \varepsilon_i \qquad (1)$$

where $y_i = 1$ indicates behaviour (Hypothesis 1) or loyalty (Hypothesis 2) of subject i, variable $Treat_i$ stands for treatment assignment, coefficient β is estimated treatment effect, vector X_i^n includes a set of additional explanatory variables and γ_n is a vector of their respective coefficients.

4. Experimental Results and Analysis

4.1 General results

The first analysis consists in understanding how users reacted to the experiment in general. There were 398 valid observations, and the distribution is displayed in Table 2.

Table 2.

Outcome of the experiment per group.

	Group	
Did the user make a ride?	**Control**	**Treatment**
No	181	168
Yes	17	32

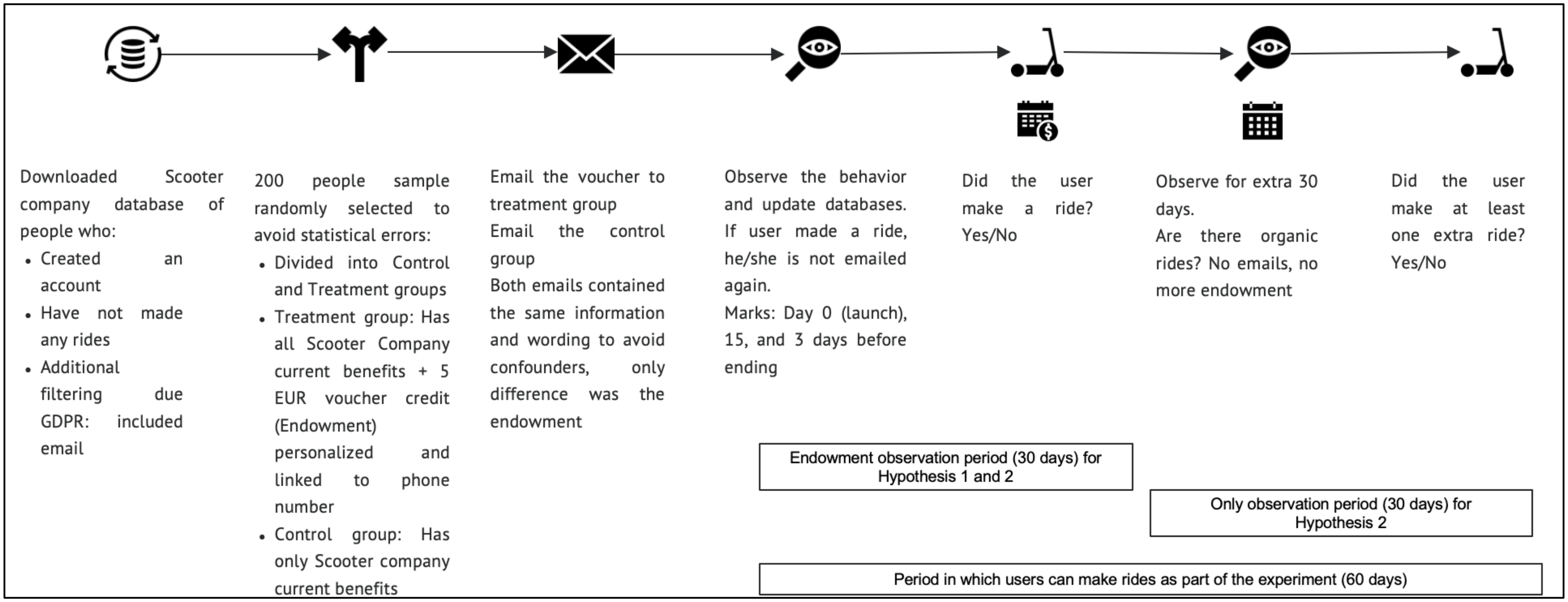
The conversion rate refers to the percentage of individuals who transitioned from intending to use the scooter to actually using it. In both rounds combined, the treatment group had a conversion rate of 16% (32 people), while the control group had a rate of 8.6% (17 people). Overall, 12.3% (49 people) of participants made their first ride during the first month of observation.

Since only the members of the treatment group received a monetary endowment, the company invested 160 EUR. Figure 3 illustrates the total turnover per rider, which amounted to 606.88 EUR in sales throughout the experiment's duration.

Analysing Figures 3 and 4, it is notable that users in the control group - particularly those from Estonia - had the highest turnover and the most significant number of rides, with individual values of 64.80 EUR and 126 journeys taken, respectively. However, it is important to highlight that users in the treatment group needed to utilize the entire five euro voucher before their turnover could be counted.

Figure 2.

Designed experiment dynamics



The experiment was design in two rounds initially due budget constraints, consequently, it is important to analyse the results according to each of the rounds. Figure 5 shows, that the treatment and control groups in round 1 had a conversion rate of 18% and 4.0%, respectively, a difference of 14 p.p. in favour of the treatment group. With the inclusion of additional participants in the second round, we observe a conversion rate in the treatment group of 14% and 13% in the control group, a difference of 1 p.p.

This descriptive comparison indicates a strong round effect; therefore, a categorical indicator variable was included in the model to measure the impact of being part of the first or second round. As part of the general results in Appendix C, it is observed that all users who made a ride from the treatment group used the service at least one more time; meanwhile, two control group users only used the service once during the observation period. An extract of Appendix C is depicted in table 3 for the top 10 users organized by number of rides made.

Overall, the company invested 160 EUR in endowment vouchers, and in general the experiment had a return on investment of 280%. This means that for every euro invested they got back 2.8 euros in new sales, but what is most important is the increment in user adoption.

Table 3.

Extract of Appendix C. Top 10 users who transitioned from intention to behaviour.

Rider ID	Number of rides	Total turnover (EUR)	Group	Days passed until first ride
23	126	14.89	Control	5
8	52	64.79	Control	338
1	49	49.32	Control	10
3	47	34.6	Control	160
2	31	48.21	Treatment	57
32	21	33.68	Control	99
35	14	13.65	Control	92
29	13	36.16	Treatment	28
28	11	16.27	Control	382
26	10	9.6	Treatment	362

Figure 3.

Total turnover per user who demonstrated behaviour

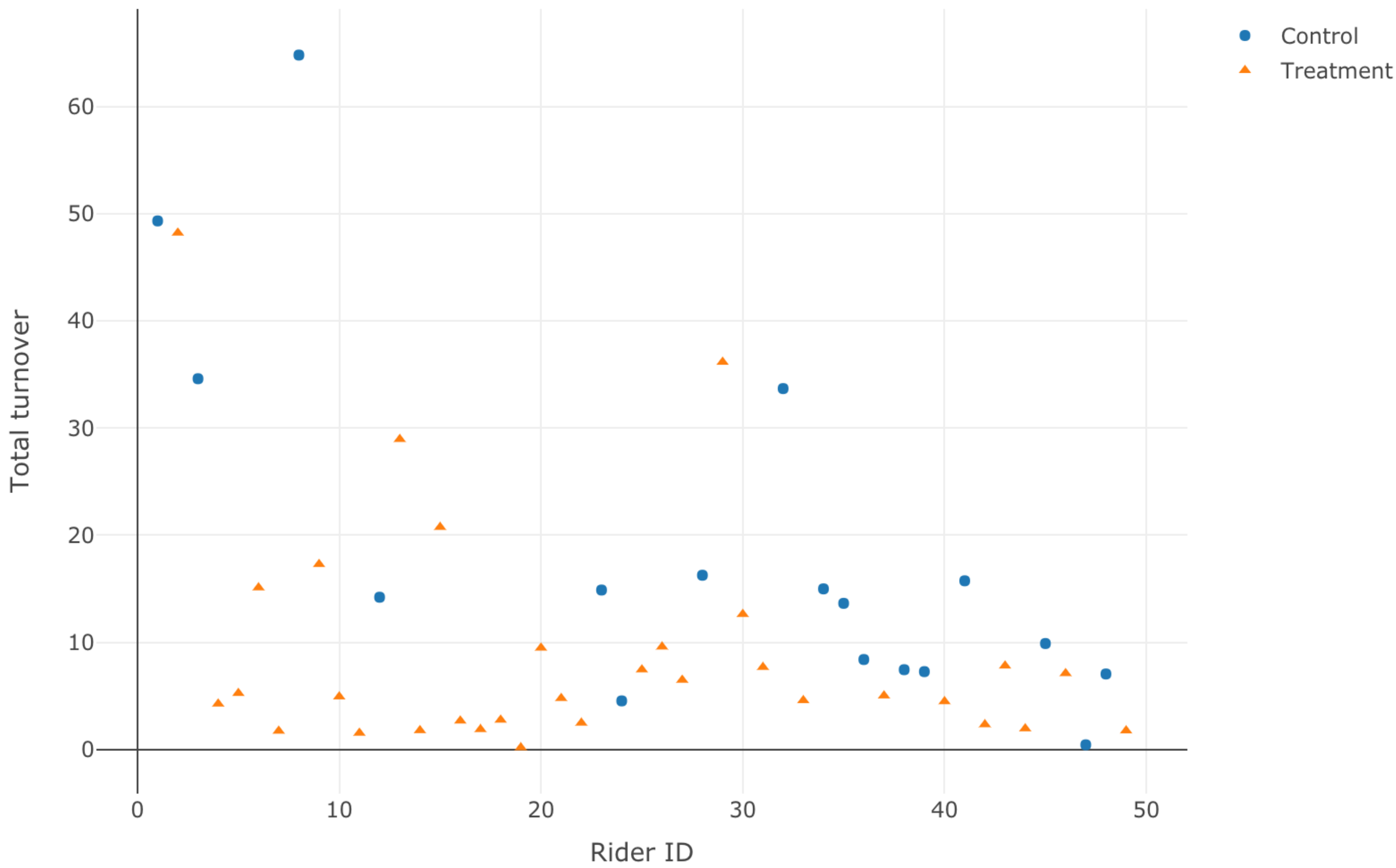


Figure 4.

Total number of rides per user who demonstrated behaviour

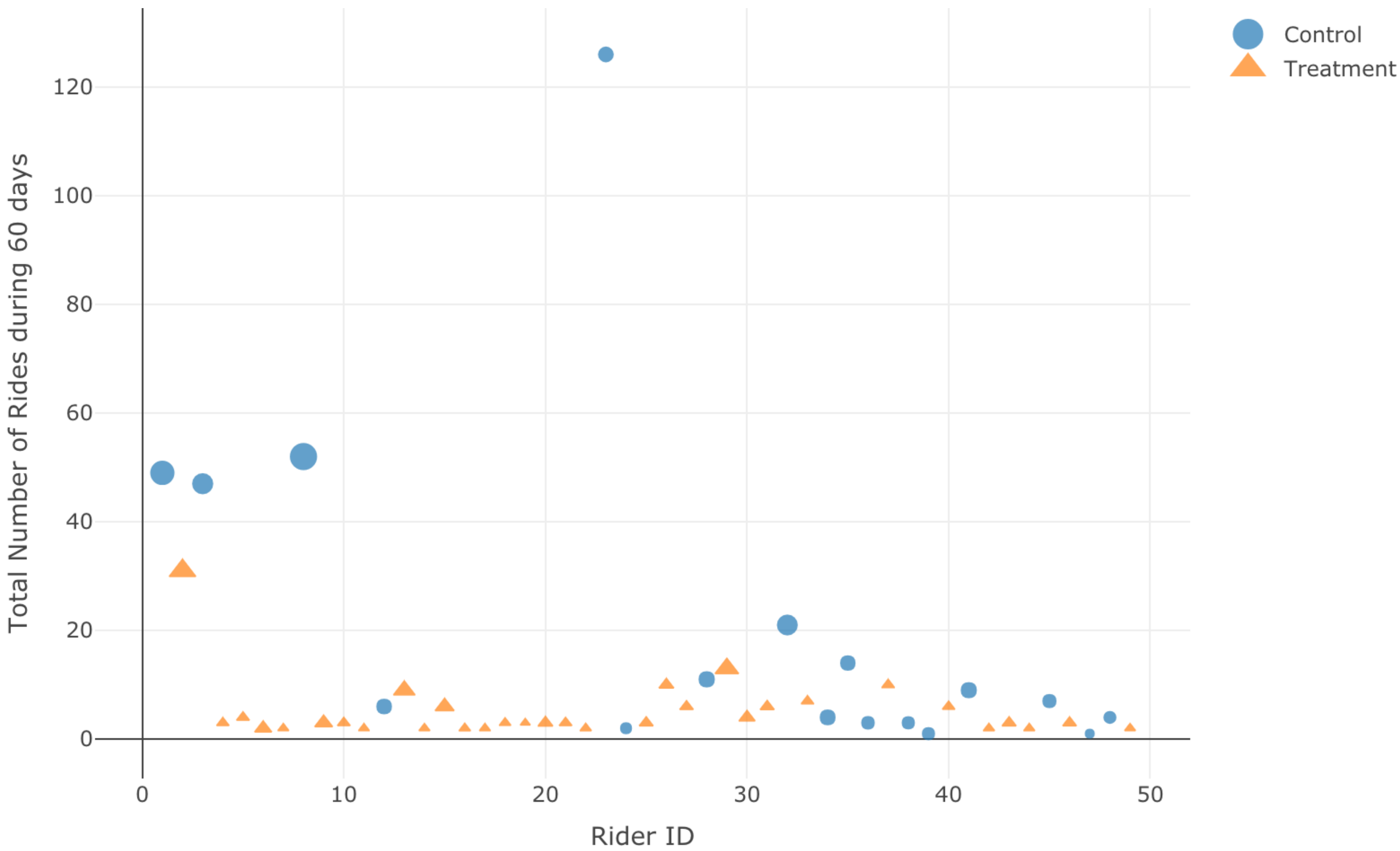
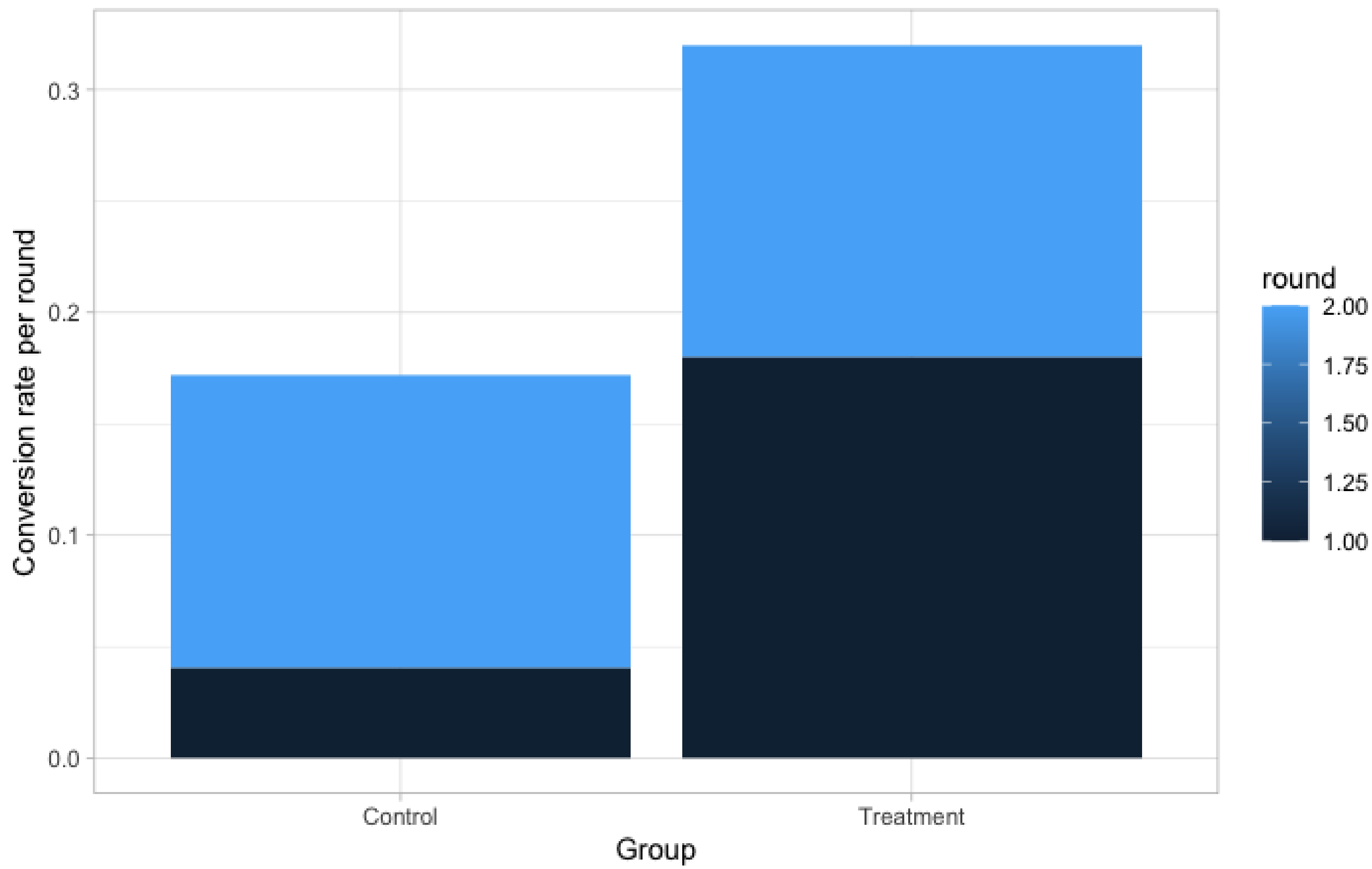


Figure 5.

Outcome of the experiment per group and round



4.2 Hypothesis 1: Adding an endowment effect will incentivize users to utilize the service

4.2.1 Logistic regression results and analysis for Hypothesis 1.

The first proposed model aims to examine the impact of the endowment on the treatment group compared to the control group in both rounds. Additionally, it seeks to determine whether the inclusion of a five euro voucher makes a difference in the transition from intention to behaviour. The treatment and outcome variables, which indicate whether a person received an endowment and whether they made a ride or not, follow a logistic (1,0) distribution. For both logit and probit links, a logistic regression model of the binomial family was implemented. Subsequent discussions will consider the results obtained from both types of models.

The initial step involves conducting a Likelihood Ratio Test (LR Test) to assess the significance of the model outcomes for the experiment. In the LR Test, the null hypothesis assumes that all model parameters, except the intercept, are zero, while the alternative hypothesis suggests that at least one parameter significantly differs from zero. For both the logit and probit models, the p-values are lower than 0.05, specifically 4.43e-05 for the logit model and 5.869e-05 for the probit model. As a result, we can reject the null hypothesis, indicating sufficient evidence to claim that at least one explanatory variable is not zero, and that the selected models yield significant results.

We aggregated the data from both rounds to analyse the experiment and all the participants. Now, our next step is to assess whether the logistic regression model accurately captures the relationships in the data. To do this, we utilized a Hosmer-Lemeshow test to test the null hypothesis, which aims to demonstrate that there are no significant differences between the observed and expected values.

The p-values of both models are greater than 0.05, with the logit model having a p-value of 0.7716 and the probit model having a p-value of 0.59. As a result, there is insufficient evidence to reject the null hypothesis, indicating no systematic differences between observed and expected values, and the models fit the data well.

The McFadden's pseudo R^2 for logit and probit models is 0.1000973 and 0.09792786, respectively. In logistic regression models, this value tends to be lower in comparison with linear regression models (Menard, 2002), and considering the sample size of the experiment, both values are moderate representations of the goodness of fit.

Table 4 provides estimation results of both models for Hypothesis 1 using Generalized Linear Models (GLM). When interpreting the results of GLM, it is often more insightful to focus on comparing the signs and relative sizes of the estimated coefficients rather than their exact values. This is because the link function (logit/probit) used in the model transforms the response variable, leading to a more intricate relationship between the response and predictor variables than a straightforward linear relationship. Consequently, the precise numerical values of the coefficients may not be directly comparable or convey meaningful information.

We initially analyse the positive responses in both models. The "Group Treatment" variable is a categorical variable indicating whether a participant belongs to the treatment group or the control group. The "Round 2" variable is another categorical variable representing whether a participant is in the second round or the first.

The treatment variable is found to be positive and statistically significant at $p<0.01$, indicating that belonging to the treatment group increases the probability of users making a ride compared to the control group. Additionally, the round 2 variable is positive and statistically significant at $p<0.1$, suggesting that being part of round 2 increases the probability of making a ride compared to round 1.

Upon analysing the variables with a negative sign, we found that the "days until first ride" variable is negatively and significantly associated at $p<0.01$. This implies that as the duration between sign-up and the first ride increases, the probability of using the service decreases. Additionally, a similar pattern emerges when comparing the "Country" variable, specifically between Latvia and Estonia. If the service is used in Latvia, there is a negative impact compared to when it is used in Estonia, which is the base category.

There are additional variables that require analysis within the model, specifically the non-linear component and the interaction between group and round discussed in section 4.1. To account for non-linearity, a cubic term called "days_until_first_ride3" is introduced as an additional explanatory variable. The estimations for this term are 3.3e-08 in the logit model and 1.6e-08 in the probit model, both of which are statistically significant at $p<0.1$. Furthermore, the interaction variable "groupTreatment:Round2" effectively captures the significant differences in conversion rates observed between groups when they were involved in a specific round. The coefficients are negative and statistically significant at 5% and help us confirm the “round effect”, as we observe that the effect of the monetary endowment in round 2 is weaker compared to when it is given in round 1.

Table 4.

Hypothesis 1 logit and probit model coefficient comparison.

	Dependent variable: Did Make a Ride or Not	
	logistic (1)	**probit (2)**
Group Treatment	1.669***	0.813***
	(0.585)	(0.280)
Round 2	1.008*	0.482*
	(0.609)	(0.293)
Days until first ride	-0.010***	-0.005***
	(0.003)	(0.002)
I(Days until first ride ^3)	0.00000*	0.00000*
	(0.00000)	(0.000)
Country Latvia	-0.496	-0.300
	(0.406)	(0.230)
GroupTreatment:Round2	-1.624**	-0.776**
	(0.723)	(0.362)
Constant	-1.701***	-0.937***
	(0.619)	(0.309)
Observations	398	398
Log Likelihood	-133.625	-133.947
Akaike Inf. Crit.	281.251	281.895
Note:	*p<0.1; **p<0.05; ***p<0.01	

To quantify the results, we employ odds ratio analysis with a 95% confidence interval, which is presented in Table 5 for the logit model. The analysis reveals that users in the treatment group have a significantly higher probability of making a ride compared to those in the control group.

Table 5.

Hypothesis 1 Odds Ratio (OR) and confidence intervals for logit model.

		Confidence intervals	
Control Variable	**OR**	**2.5%**	**97.5%**
(Intercept)	0.1824267	0.04725378	0.5616580
Group Treatment	5.3055774	1.84195886	19.3081689
Round 2	2.7388919	0.88984794	10.2974231
Days until first ride	0.9902357	0.98370505	0.9966691
I(Days until first ride ^3)	1.0000000	1.00000000	1.0000001
Country Latvia	0.6092311	0.26937475	1.3352584
GroupTreatment:Round2	0.1971688	0.04329187	0.7696712

Treatment group subjects have 5.3 times greater odds of making a ride than those who did not receive the endowment. The control variable round also demonstrates that a user who belongs to round 2 has 2.7 times greater odds of making a ride compared to users in round 1, independently of the type of group.

Control variable days_until_first_ride has an odds ratio coefficient lower than 1; therefore, if it increases by 1 unit, the probability of making a ride decreases, and the odds of making a ride decrease by 0.98% (1-0.9902357). Similar situation with variable country, if the subject belongs to Latvia, the probability of making a ride decreases along with the odds by 0.39% (1-0.6092311) with respect to the case as if the user is part of the country Estonia.

When considering the non-linear and interaction variables, we find that there is no discernible difference in the odds of the outcome concerning "days_until_first_ride3". The coefficient value of 1 suggests that the odds of making a ride are similar for both the control and treatment groups. However, the coefficient estimate for the interaction term reveals an additional effect on the log-odds of making a ride when both "Group Treatment" and "Round 2" are present. This coefficient is positive and statistically significant, indicating that participants in the treatment group who are in the second round have 2.9 times higher odds of making a ride compared to participants in the treatment group who are in round 1.

Table 6.

Hypothesis 1 Average Marginal Effects (AME) for logit model.

Control Variable	AME	SE	z	p	Lower CI	Upper CI
Country Latvia	-0.0459	0.0358	-1.2831	0.1995	-0.1160	0.0242
Days until first ride	-0.0004	0.0002	-2.6276	0.0086	-0.0008	-0.0001
Group Treatment	0.0696	0.0323	2.1596	0.0308	0.0064	0.1329
Round 2	-0.0048	0.0322	-0.1497	0.8810	-0.0678	0.0582

The Average Marginal Effects (AME) of the logit model regression for the Group variable in Table 6 indicates that receiving an endowment increases the probability of making a ride, on average, by 6.96 percentual points compared to those who did not. Meanwhile, regarding days until the first ride the AME is negative 0.04 percentual points, for every day that passes the probability for a user to transition from intention to behaviour decreases when only considering that specific control variable. Both previous results are statistically significant at 95%. In addition, Round 2 and Country Latvia have an AME of -

0.48 percentual points and -4.59 percentual points, respectively. Nevertheless, with respect to the AME analysis those results include the value of zero in their confidence interval.

According to the probit model AME results shown in Table 7, the Group variable indicates that being in the treatment group increases the probability of making a ride by an average of 6.82 percentage points, compared to those in the control group, at a 10% significance level. In this case, the confidence interval includes the value of zero, and we cannot reject the possibility that there is no effect or difference between the groups. Nevertheless, the fact that the confidence interval also includes positive values suggests some evidence supporting a positive effect of the endowment effect and its influence on the subjects' behaviour. Variable Round 2 has an AME of -0.08 percentual points; meanwhile, the AME in the probit model for days until first ride and country Latvia are -0.04 and -5.11 percentual points, respectively.

Table 7.

Hypothesis 1 Average Marginal Effects (AME) for probit model.

Control Variable	AME	SE	z	p	Lower CI	Upper CI
Country Latvia	-0.0511	0.0382	-1.3401	0.1802	-0.1259	0.0236
Days until first ride	-0.0004	0.0003	-1.3554	0.1753	-0.0010	0.0002
Group Treatment	0.0682	0.0360	1.8921	0.0585	-0.0024	0.1388
Round 2	-0.0008	0.0341	-0.0224	0.9821	-0.0677	0.0661

4.2.2 Prediction capabilities and model performance analysis for Hypothesis 1.

To comprehensively analyse the obtained results, it holds significant importance to assess the performance of the model and its predictive capabilities, ensuring reproducibility. This evaluation becomes crucial if the micromobility company intends to employ the model on a larger population for making informed business decisions.

The confusion matrix depicted on Figure 6 and described in Table 8 help us understand the distribution of the prediction based on the logit regression for Hypothesis 1. The model correctly predicted 28 true positives, meaning that in cases where the model predicted a user would make a ride, they did indeed make a ride. It also correctly predicted 253 true negatives, meaning that in cases where the model predicted a user would not make a ride, they did not. However, the model also made 21 false negatives, indicating that 21 users would not ride when they did, and 96 false positives predicted that 96 users would make a ride when they did not. The model's sensitivity, or ability to correctly identify positive cases out of all the actual positive cases, is 57.1%. However, the model's specificity, or ability to correctly identify negative instances out of all the real negative cases, is higher, with a value of 72.5%. Overall, the model's accuracy is 70.6%.

Figure 6.

Confusion matrix for logit model in Hypothesis 1.

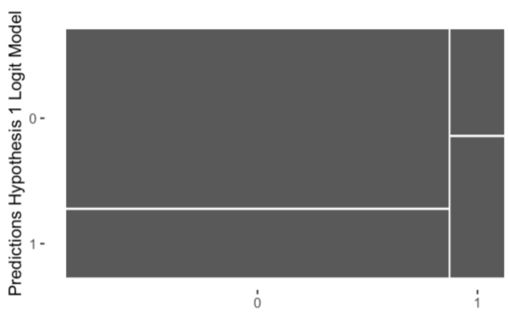


Table 8.

Confusion matrix results for logit model in Hypothesis 1.

Predictions Hypothesis 1 Logit Model	Did not make a ride	Did make a ride
Predicted No Ride	253	21
Predicted Ride	96	28

Table 9.

Performance logit model in Hypothesis 1.

Metric	Estimator	Estimate for Logit Model
Accuracy	binary	0.7060302
Sensitivity	binary	0.5714286
Specificity	binary	0.7249284

The same analysis and tables were created for the probit model, with the confusion matrix shown in Figure 8, the distribution of which is detailed in Table 10, and its performance is estimated in Table 11. Compared to the logit model, the probit model has lower accuracy and specificity, with values of 69.6%

and 71.4%, respectively, and similar sensitivity to the logit model in identifying positive cases, with a value of 57.1%. The classification resulted in 249 subjects identified as true negatives, 28 as true positives, 21 as false positives, and 100 as false negatives.

Figure 7.

Confusion matrix for probit model in Hypothesis 1.

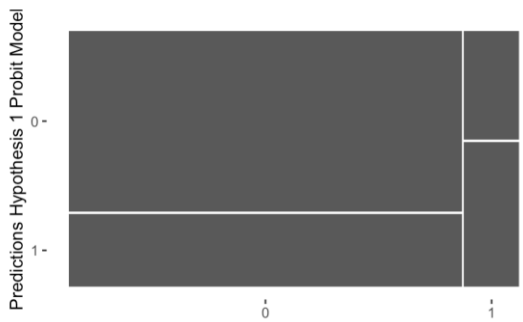


Table 10.

Confusion matrix results for probit model in Hypothesis 1.

Predictions Hypothesis 1 Probit Model	Did not make a ride	Did make a ride
Predicted No Ride	249	21
Predicted Ride	100	28

Table 11.

Performance probit model in Hypothesis 1.

Metric	Estimator	Estimate for Logit Model
Accuracy	binary	0.6959799
Sensitivity	binary	0.5714286
Specificity	binary	0.7134670

The Receiver Operating Characteristic curve (ROC) allows to graph and compare the performance of the logistic regression model. Figure 8 compares the ROC for the logit model (red line) and probit model (green line), values of Area Under the Curve (AUC) of 0.721186 and 0.721244, respectively. These measurements are provided in detail in Table 12.

Figure 8.

ROC for probit and logit models of Hypothesis 1.

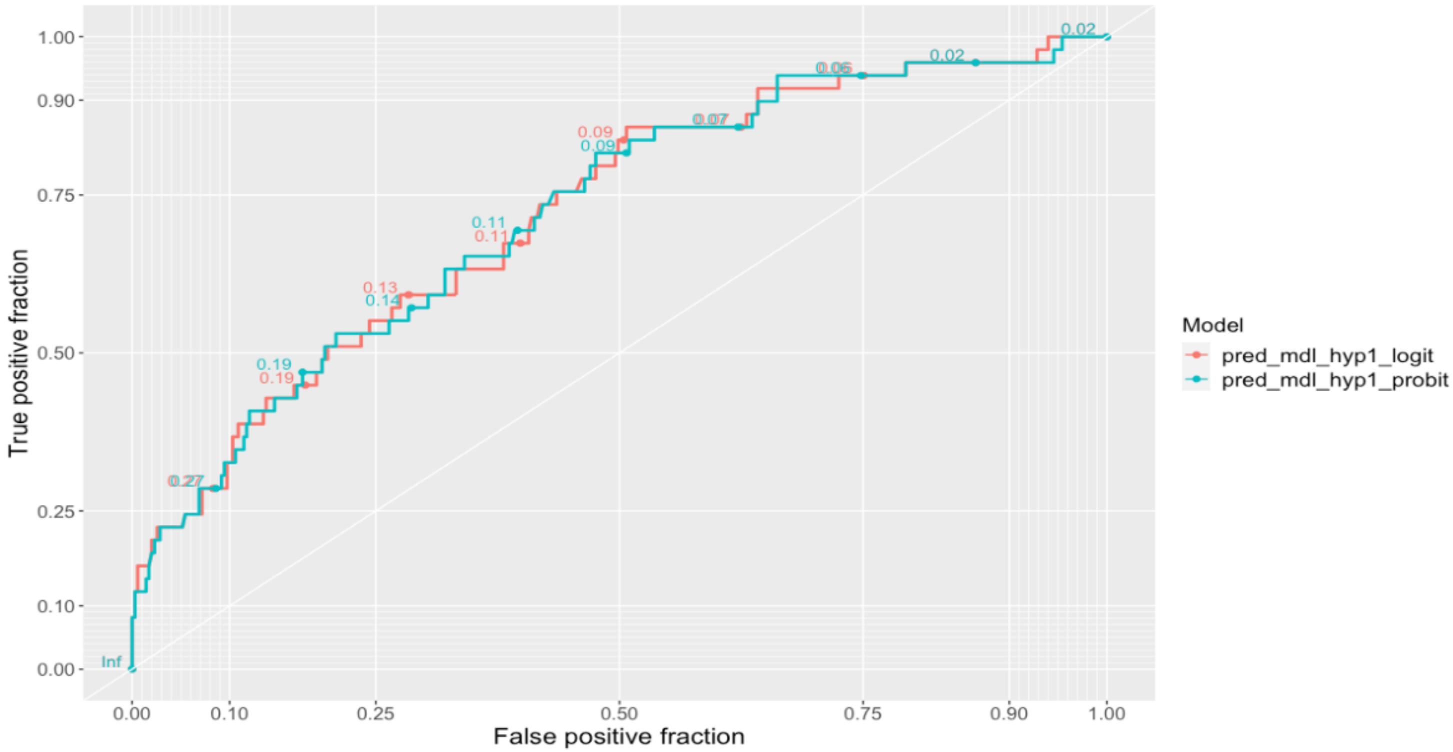


Table 12.

AUC Table for logit and probit models for Hypothesis 1.

Hypothesis 1 Model	AUC
Logit	0.7211859
Probit	0.7212444

4.3 Hypothesis 2: Endowment effect will increase user's loyalty toward the service

4.3.1 Logistic regression results and analysis for Hypothesis 2.

In Figure 1, we observe the relevance of the results of the first hypothesis in relation to the second hypothesis. A user received a special benefit (monetary endowment) and actually used it; shows they went from just thinking about using the service to actually taking action. That same user may or may not have continued using the service after their initial experience. The second hypothesis aims to explore whether individuals who received the special benefit (endowment) demonstrate higher levels of loyalty by engaging in more rides compared to those who did not receive the benefit. This comparison helps us understand how monetary endowments affect people's loyalty towards the service, and it's an important aspect to consider in our research.

The model introduces a new binary variable to answer the question, *"did the user make more than one ride?."* This variable is derived from the findings of Hypothesis 1. If a user engages in multiple rides following their initial experience, we interpret it as an indication of loyalty. Conversely, if a user either does not take any additional rides or only performs a single initial ride, it suggests that the endowment effect did not generate loyalty among the participants during the experiment.

For Hypothesis 2 we follow the same principles and initial tests described in section 4.2.1; the LR Test p-value for the logit model is 2.82e-05, and for the probit model, 3.93e-05, being both lower than 0.05, provides enough evidence to conclude that our model proposed does explain that at least one explanatory variable is not zero and our results are significant.

The Hosmer-Lemeshow test will describe how well the logistic regression model captures parts of the distribution and fits the data. In this test, the models have p-values higher than 0.05, which is expected; the logit model has a p-value of 0.52 and the probit model has a p-value of 0.66. None of those results provide sufficient evidence to reject the null hypothesis for this type of test, which allows us to continue analysing our results.

The McFadden's pseudo R^2 for logit and probit models is 0.091 and 0.089, respectively. Similar to Hypothesis 1, both values are moderate representations of the goodness of fit, considering the experiment's sample size and the type of regressions.

The comparison of coefficients, signs, and significance of the variables used in the model is presented in Table 13, encompassing both the logit and probit models. Among the various variables examined, Group and Round demonstrate positive effects on the likelihood of users making additional rides.

However, it is important to note that only the Group variable achieves statistical significance. The results indicate that users belonging to the treatment group have a higher probability of engaging in additional rides compared to those in the control group.

The variable days until first ride does continue having a negative impact compared to the results for Hypothesis 1 in table 4, which means that for every additional day a user does not use the services, the lower the probability of them doing so.

Table 13.

Hypothesis 2 model logistic model coefficient comparison.

	Dependent variable: Did make more than one ride	
	logistic (1)	**probit (2)**
Round 2	0.960 (0.611)	0.468 (0.290)
Group Treatment	1.625*** (0.579)	0.802*** (0.277)
Days until first ride	-0.004*** (0.001)	-0.002*** (0.001)
GroupTreatment: Round 2	-1.382* (0.728)	-0.676 * (0.363)
Constant	-2.277*** (0.551)	-1.275*** (0.258)
Observations	398	398
Log Likelihood	-131.392	-131.747
Akaike Inf. Crit.	271.783	273.495
Note:	*p<0.1; **p<0.05; ***p<0.01	

To provide a quantitative assessment of the results, an odds ratio analysis for the logit model is presented in Table 14. According to the analysis, users belonging to the treatment group exhibit 5.1 times greater odds of making an additional ride compared to those in the control group. This conclusion is supported by the fact that the confidence interval does not include the value of zero, indicating a statistically significant effect.

Furthermore, users participating in the second round have 2.6 times greater odds of making an additional ride than users in the first round. On the other hand, the "days until the first ride" variable has an odds ratio of 0.996, suggesting that the probability of making an extra ride decreases by 0.40% (1 - 0.9959347) for each additional day of delay.

The interaction variable between Group Treatment and Round reveals that if a user belongs to the treatment group in round 2, their probability of making an additional ride is higher, with 3.3 times greater odds compared to those in the treatment group in round 1.

Table 14.

Hypothesis 2 Odds Ratio (OR) and confidence intervals for logit model.

		Confidence intervals	
Control Variable	**OR**	**2.5%**	**97.5%**
(Intercept)	0.1025531	0.02959656	0.2702696
Group Treatment	5.0796811	1.78336137	18.3055157
Round 2	2.6113790	0.84133231	9.8224257
GroupTreatment:Round2	0.2510576	0.05487455	0.9947565

The AME for Group variable in Tables 15 and 16 shows that individuals who receive an endowment effect have a higher probability of making an extra ride by 7.9 and 7.7 percentage points, on average, compared to those part of the control group, in the logit and probit model, respectively. Both are statistically significant at 95%.

Concurrently, the *round* variable increases the probability by 0.3 percentual points in the logit model and 0.6 percentual points in the probit model, on average, for users in round 2 rather than when they are part of round 1. While the confidence interval for the Round variable includes the value of zero, indicating a possibility of no effect or difference between the groups, the fact that positive values are also included suggests some evidence of a positive effect on the behaviour of the subjects with respect to their participation in different rounds.

In both models, the probability of making an extra ride decreases by an average of -0.04 percentage points for each additional day that passes as indicated in both tables for the "days until the first ride" variable.

Table 15.

Hypothesis 2 Average Marginal Effects (AME) for logit model.

Control Variable	AME	SE	z	p	Lower CI	Upper CI
Days until first ride	-0.0004	0.0001	-3.7097	0.0002	-0.0006	-0.0002
Group Treatment	0.0790	0.0310	2.5477	0.0108	0.0182	0.1398
Round 2	0.0030	0.0314	0.0967	0.9230	-0.0584	0.0645

Table 16.

Hypothesis 2 Average Marginal Effects (AME) for probit model.

Control Variable	AME	SE	z	p	Lower CI	Upper CI
Days until first ride	-0.0004	0.0001	-3.7215	0.0002	-0.0006	-0.0002
Group Treatment	0.0767	0.0311	2.4664	0.0136	0.0157	0.1377
Round 2	0.0061	0.0313	0.1955	0.8450	-0.0553	0.0675

4.3.2 Prediction capabilities and model performance analysis for Hypothesis 2.

Similarly to what was done in section 4.2.2, we analyse the prediction power and performance of the classification model for Hypothesis 2. Figure 9 and table 17 represent the distribution of the predictions based on the logit regression.

The model classified accurately as true negative a total of 261 subjects, people who did not make a ride or only did one. As true positives, the model classified 25 subjects who did make a ride and made more than one. However, there were 22 false positives and 90 false negatives in the classification.

The model's overall performance is estimated in table 18, showing an accuracy of 71.9%, a sensitivity of 53.2%, and a specificity of 74.4%. These metrics indicate that the model correctly predicted the outcome for most of the subjects, but there is room for improvement in correctly identifying positive cases. The sensitivity reflects the model's ability to correctly detect subjects who made more than one ride, while the specificity represents its ability to correctly identify subjects who did not make more than one ride.

By analysing the prediction power and performance of the classification model, we can assess its effectiveness in predicting the behaviour of the subjects and draw conclusions about the relationship between the variables and the outcome of interest.

Figure 9.

Confusion matrix for logit model in Hypothesis 2.

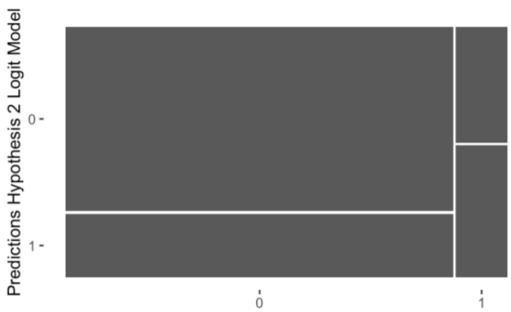


Table 17.

Confusion matrix results for logit model in Hypothesis 2.

Predictions Hypothesis 2 Logit Model	Did not make a ride or only 1	Did make a ride and more than 1
Predicted No Ride or only 1	261	22
Predicted Ride and more than 1	90	25

Table 18.

Performance logit model in Hypothesis 2.

Metric	Estimator	Estimate for Logit Model
Accuracy	binary	0.7185930
Sensitivity	binary	0.5319149
Specificity	binary	0.7435897

Figure 10 and Table 19 are based on the probit regression for Hypothesis 2. The true negative value comprises 261 subjects, while the true positive value consists of 26 users who not only made a ride but also made more than one. Finally, the model classified 21 and 90 subjects in each category as false positives and false negatives, respectively. Table 20 displays the model's accuracy of 71.9%, sensitivity of 55.3%, and specificity of 74.1%.

Figure 10.

Confusion matrix for probit model in Hypothesis 2.

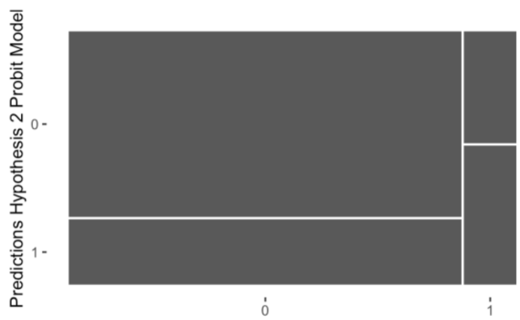


Table 19.

Confusion matrix results for probit model in Hypothesis 2.

Predictions Hypothesis 2 Probit Model	Did not make a ride or only 1	Did make a ride and more than 1
Predicted No Ride or only 1	261	21
Predicted Ride and more than 1	90	26

Table 20.

Performance probit model in Hypothesis 2.

Metric	Estimator	Estimate for Probit Model
Accuracy	binary	0.7185930
Sensitivity	binary	0.5531915
Specificity	binary	0.7407407

Although both models demonstrated an accuracy of 71.9%, the prediction of true negatives was more accurate than the classification of true positives in both models. The performance of the models for Hypothesis 2 can be compared using the ROC curves and their respective AUC values, as shown in Figure 11, and detailed in Table 21. The results reveal that the logit model outperformed the probit model with a higher AUC value.

Figure 11.

ROC for probit and logit models of Hypothesis 2.

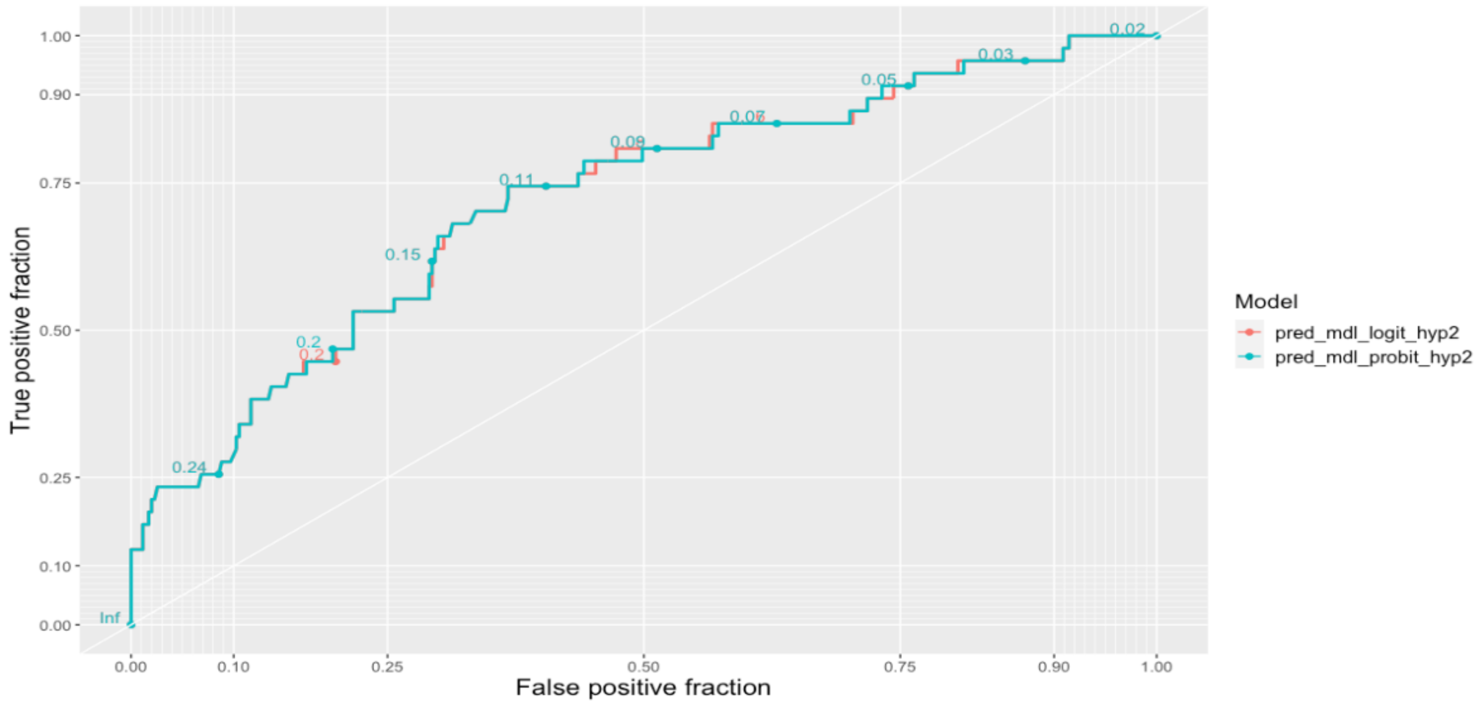


Table 21. AUC Table for logit and probit models for Hypothesis 2

Hypothesis 2 Model	AUC
Logit	0.7181003
Probit	0.7179790

5. Conclusions and recommendations.

This paper examines the influence of behavioural economic principles on users' decision-making regarding electric scooter usage. The study focuses on two key aspects of users' behaviour: their inclination to use the service when presented with new information and their loyalty to the service based on their previous experiences. In collaboration with a micromobility company based in Estonia, we identified 400 individuals who had downloaded the company's application, created profiles, but had not yet utilized the service. As part of a natural field experiment, half of the participants (treatment group) received a monetary endowment of five euros in addition to the standard benefit package, while the other half (control group) received only access to the standard benefits.

Our findings indicate that adding an endowment effect to a treatment group results in 5.31 times greater odds of a user making a ride and a positive marginal effect in which the probability increase by 6.82 percentage points on average, both statistics compared to the control group. The analysis of loyalty or fairness perceived by the users towards the company, approximated as subjects' subsequent rides after their first experience, indicate significant positive effect of endowment. Results demonstrate that users in the treatment group have 5.08 times greater odds of using the service at least one more time than those in the control group.

Since the experiment was conducted in two rounds – June-July and July-August 2022 – we additionally control for a seasonal effect. Despite both rounds were conducted in Summer, scooter use intensity may correlate with usual timing of school and university examinations, as well as vacations, hence seasonality may still affect the results. Specifically, our findings regarding the impact of the endowment effect on motivating subjects to use the scooter for the first time reveal that participants in the treatment group during the July round exhibited 2.9 times higher odds of making a ride compared to their counterparts in the treatment group during the June round. Furthermore, when considering loyalty observations, users in the treatment group during round 2 displayed 3.33 times greater odds of making an additional ride compared to those in the same group during round 1. For both hypotheses, the odds of making a ride and demonstrating loyalty are higher when a monetary endowment is introduced during the month of July compared to June.

Our study makes a valuable contribution to the existing literature by offering insights into the behaviour of users of e-scooter services within a natural field experiment. To the best of our knowledge, this is the first study to experimentally investigate the influence of endowments on users' initial adoption of micromobility services and their subsequent loyalty to the service provider, by revealing that a monetary endowment effect leads to higher odds of users transitioning from just intention to actual behaviour and loyalty.

Hence, the results of this study can be applied beyond the micromobility sector, as the key finding of the research states that a simple one-off pro-customer intervention in the form of five Euro voucher nudges otherwise hesitant customers to use the service. Since the endowment intervention tested in the paper can be similarly implemented in many other business services (any e-commerce service), as well as various public domains, including public transportation. The latter is especially important area where the results of the study can be used a starting point for further, more specific, research on how to nudge residents to use public transport, as opposed to other means of within-city transportation. Given that, in our experiment, the users responded positively to the simple monetary nudge, similar nudging scheme may be tested and applied in public transportation. The latter may also involving a small monetary endowment in the form of monthly bonus to the public transport payment card for the users, who demonstrate loyalty by making certain number of public transport rides per month. Given immense technical complexity and relatively high cost of running field experiment or randomized control trial involving public transportation system, the results of this results are of high policy relevance, as they test similar nudging mechanism in a much more simplified and less costly setting.

Given strict financial constraints, our results rely on relatively small sample size, yet sufficient one to derive empirically robust and economically meaningful results. In addition, the micromobility company may find of interest that the logit model has statistically significant results at 5% for AME, odds ratio analysis, and higher accuracy, or at least the same. These statistical tests indicate high robustness of the results albeit relatively restricted sample size; information that can be used to plan their further action plans and gain additional market plus loyal users.

For the future research on the topic, we recommend increasing the sample size in a natural field experimental setting and ensure more socio-demographic variation of the subject pool. Moreover, it shall be of interest to repeat the experiment utilizing continuous variables instead of categorical ones, as it will allow to investigate how the amount of monetary endowment affects users' behaviour and identify the optimal endowment size, which will maximize company’s profits by generating more service use and higher loyalty.

Another possible direction for future research would be to modify the experimental design to allow users to provide feedback directly through a questionnaire. In this case, users would be aware that they are being observed, which could potentially influence their behaviour by inducing experimental demand effect.

To conclude, the monetary endowment effect could be explored in other means of transportation such as subscription e-bike models which is impacted by similar variables. A service like the one mentioned competes with traditional bicycles and same users may find hesitant the motivation to transition to an electric bike, even when they are already consumers of a rental bike service.

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Appendix A. User outreach options.

Three different approaches were considered to contact users in both groups. The first method was using push-up notifications within the application. Second option was to modify the on-boarding of users when installing the application. Third option was to reach via email.

a. Push-up notifications.

Sending instantaneous messages through the application is a preferred method of electronically reaching an audience. However, there were two specific challenges when using this method for our experiment. Firstly, the audience we targeted consisted of individuals who had downloaded the application but had not yet used it. This posed a high risk, as it was possible that some individuals had uninstalled the application since downloading it, and the message may not reach the intended audience. The second challenge was technical in nature. During the experiment, push-up notifications could not be targeted to specific users, and instead were sent out to the entire population. This lack of targeting meant that it would not have been possible to distinguish between the treatment and control groups, and the approach would not have been approved due to budget restrictions, either.

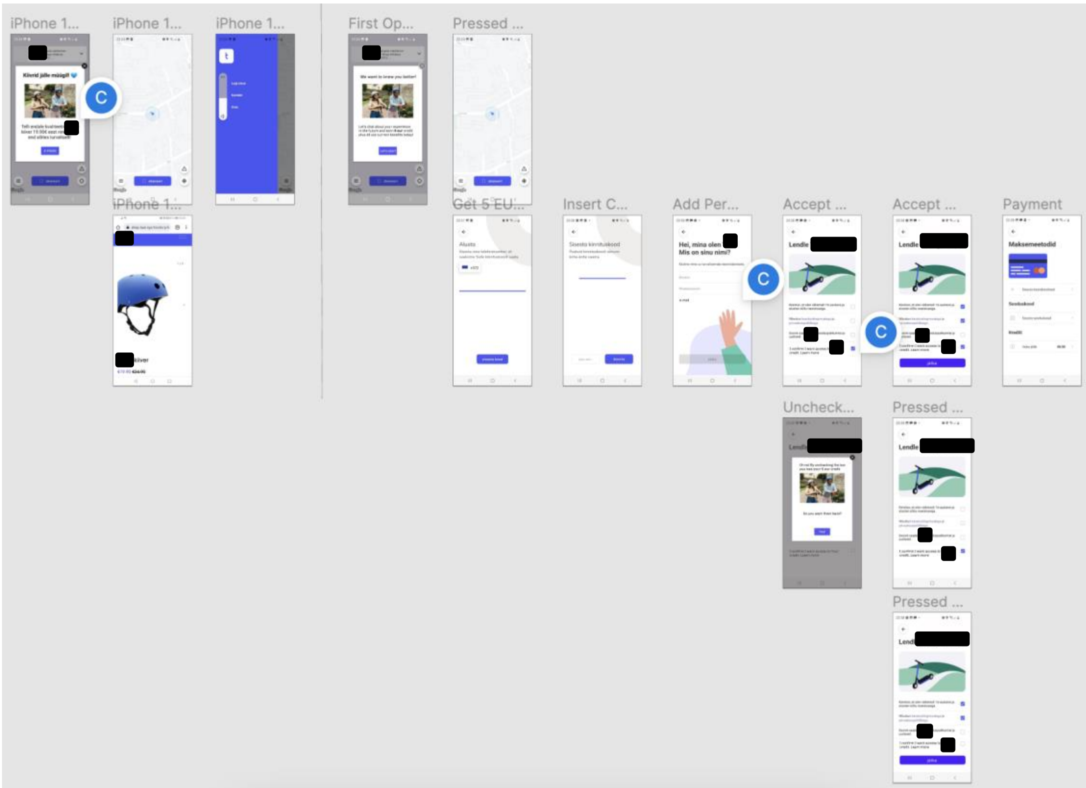
b. Modification of on-boarding experience.

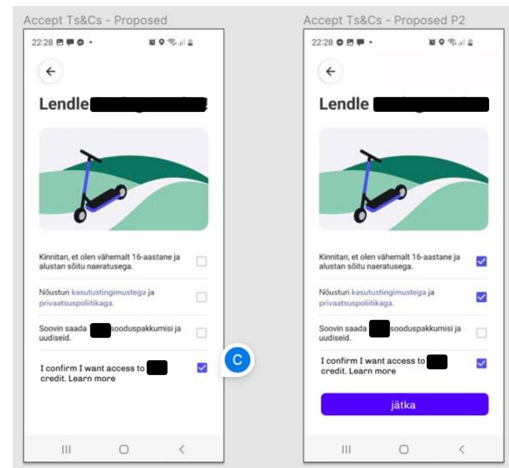
For this method a new on-boarding flow was created and presented to the General Manager and Marketing Head of the company and it is depicted in Figure A1. It consisted in including steps in which they accept the endowment when creating their profile. The structure of the experiment would have also been different as in this case the idea would have been to motivate users to make a first ride as soon as possible in case they receive an endowment. It was also targeted, and it was going to be available for the first 100 downloads. Figure 12 shows the flow proposed, in which the user had the possibility to accept the endowment from the beginning by selecting a check box. If the user did not accept the endowment it can continue with the onboarding process. This option is not considered due the high cost involved to redesign and test the application, in addition that it increases the time a user takes to open a profile.

Figure A1.

Modification of on-boarding experience.

Right side image is the final zoomed version.





c. Electronic email.

This option was considered the most convenient since it allowed us to segregate the sample into two groups without involving engineers in the back and front-end to redesign the application. Additionally, it remained loyal to the terms and conditions accepted by the users when they installed the application. This ensured that we were not breaching any agreements or obligations. By sticking to the established terms and conditions, we were able to maintain the trust of the users and avoid any negative impact on the company's reputation. The challenges from this option are:

1. Translate the messages to Estonian, English, and Latvian.
2. Create individually 200 codes. Each code is valid for 5 euros and assigned for each specific phone number with an expiration date.
3. Send manually each email to the treatment group with the code created before.
4. Send each email from marketing team's address to the subject and remain GDPR compliant.
5. Send the reminder to the subjects, manually, during specific dates.

Appendix B. Email content.

Email sent out to the treatment group.
First email:

Subject:

Your first ride with [redacted] is on us

Body:

Dear friend of [redacted],

We noticed you have not made any rides with us and we genuinely want you to experience riding with the most sustainable e-scooter [redacted]. So here is a gift for you with 5€ of [redacted] credit. Just enter the app code [redacted] in the next 30 days and breeze along.

As it is your first ride you also can get -50% off by adding code [redacted]

We wish you enjoyable riding experiences!

Happy rides

Note: You can add both codes to the promotion section and these will apply simultaneously.

Second and third email:

Subject:

Your first ride with [redacted] is on us

Body:

Dear [redacted] friend, 🤗

Remember you still have 12 days left to enjoy your 5 EUR credit with code [redacted] and get 50% off of your first ride by using the code [redacted] 🛴

Enjoy the breeze!

Email sent out to the control group.

First email:

Subject:

Your first ride with [redacted] 50% off

Body:

Dear friend of [redacted], 🤗

We noticed you have not made any rides with us and we genuinely want you to experience riding with the most sustainable e-scooter [redacted].

As it is your first ride you can get -50% off by adding code [redacted]

We wish you enjoyable riding experiences! 🤍

Happy rides

Second email and third email:

Subject:

Your first ride with [redacted] 50% off

Body:

Dear friend of [redacted], 🤗

Remember you still can enjoy and get 50% off of your first ride by using the code [redacted] 🛴

Enjoy the breeze!

Appendix C. Number of rides and total turnover per user who demonstrated behaviour.

Table C1.

Number of rides and total turnover per user who exhibited behaviour.

Rider ID	Number of rides	Total turnover (EUR)	Group	Days passed until first ride
23	126	14.89	Control	5
8	52	64.79	Control	338
1	49	49.32	Control	10
3	47	34.6	Control	160
2	31	48.21	Treatment	57
32	21	33.68	Control	99
35	14	13.65	Control	92
29	13	36.16	Treatment	28
28	11	16.27	Control	382
26	10	9.6	Treatment	362
37	10	5.04	Treatment	91
13	9	28.96	Treatment	338
41	9	15.75	Control	102
33	7	4.6	Treatment	6
45	7	9.9	Control	12
12	6	14.22	Control	333
15	6	20.76	Treatment	335
27	6	6.5	Treatment	365
31	6	7.7	Treatment	30
40	6	4.5	Treatment	430
5	4	5.27	Treatment	9
30	4	12.64	Treatment	291
34	4	15	Control	1
48	4	7.06	Control	427
4	3	4.28	Treatment	319
9	3	17.3	Treatment	301
10	3	4.95	Treatment	48
18	3	2.78	Treatment	34

19	3	0.2	Treatment	8
20	3	9.5	Treatment	48
21	3	4.8	Treatment	284
25	3	7.47	Treatment	47
36	3	8.41	Control	69
38	3	7.46	Control	24
43	3	7.83	Treatment	91
46	3	7.12	Treatment	19
6	2	15.12	Treatment	7
7	2	1.75	Treatment	137
11	2	1.56	Treatment	416
14	2	1.8	Treatment	67
16	2	2.7	Treatment	28
17	2	1.9	Treatment	29
22	2	2.5	Treatment	63
24	2	4.55	Control	475
42	2	2.35	Treatment	191
44	2	1.97	Treatment	92
49	2	1.78	Treatment	46
39	1	7.28	Control	454
47	1	0.45	Control	38

Appendix D. Variables and models.

Table D1.

All variables and their description.

Variable name	Description
Group	Describes the group a participant belongs to: Control or Treatment
groupTreatment	Model results. This metric represents the difference in effect between being part of the treatment group and the control group. It helps to measure the impact of the treatment in relation to the absence of the treatment
Country	Describes the country assigned to the subject. Estonian, Latvian.
countryLatvia	Model results. This metric represents the difference in effect between being a customer based in Latvia with respect a customer located in Estonia.
Round	Describes the round in which a subject was part of the experiment.
roundRound2	Model results. This metric represents the difference in effect between being a subject who was part of the experiment in round 2 with respect to being part of it in round 1.
Days_until_first_ride	Days it took a user to make their first ride.
groupTreatment:roundRound2	Interaction variable. Being part of group treatment during round 2 in comparison to being part of group control.
days_until_first_ride^3	Variable to understand the non-linearity of the data.
Did make a ride	Response variable for Hypothesis 1.
Extra ride	Response variable for Hypothesis 2.

Resümee

SIHTKAPITALI EFEKT KERGETE ELEKTRISÕIDUKITE KASUTAMISEL: EKSPERIMENTAALNE UURIMUS

Carlos Antonio Quiros Duran

Tehnoloogia arengust tulenevalt on märkimisväärselt kasvanud mikromobiilsusteenuste valdkond, mille tagajärjena on asutatud mitmeid ettevõtteid, mis opereerivad erinevates linnades üle maailma. Antud ettevõtted püüavad oma turuosa laiendada ning kliendilojaalsust kujundada keskendudes põhiliselt sõidukite arvule ja hinnastrateegiale. Samas pakub kliendikeskne lähenemine võimalusi eristumiseks ja konkurentsiks, eriti kasutajate seas, kes peale hinna ja sõidukite arvu peavad oluliseks teisi tegureid.

Erinevate kasutajatüüpide seas on eristunud grupp, kes on alla laadinud konkreetse rakenduse ning loonud profiili, kuid ei ole veel kordagi teenust kasutanud. Parima kliendikogemuse pakkumiseks on ettevõtete jaoks oluline julgustada kasutajaid sõidukeid ka tegelikult kasutama. Uurimaks, kuidas raha mõjutab konkreetse inimgrupi käitumist üleminekul kavatsusest (rakenduse allalaadimine ja profiili loomine) tegudeni (teenuse kasutamine), tegime koostööd Eesti ettevõttega, mis opereerib Lätis ja Eestis. Eesmärgina uurida, kas sihtkapitali efekt („Endowment effect“) mõjutab tarbijaid teenust kasutama, viisime läbi eksperimendi uuritavate loomulikus keskkonnas. Lisaks soovisime katse käigus uurida, kas rahaline toetus võib suurendada juba sõidu teinud kasutajate lojaalsust, julgustades neid teenust vähemalt ühe korra veel kasutama.

Meie tulemused näitavad, et võrreldes kontrollrühmaga mõjutas täiendava raha andmine oluliselt tõenäosust, et uuritavad otsustaks tegelikult teenust kasutada. Lisaks viitavad tulemused, et kingitud raha mõjutas positiivselt kasutajate lojaalsust, sest raha saanute rühm näitas suuremat tõenäosust teha täiendav sõit võrreldes nendega, kes ei saanud raha.

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