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The effect of shared e-scooter programs on modal shift: Evidence from Sweden

Khashayar Kazemzadeh [a,b,*], Frances Sprei [b]

[a] Institute for Transport Studies, University of Leeds, Leeds, United Kingdom
[b] Space, Earth & Environment, Chalmers University of Technology, Gothenburg 412 96, Sweden

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ABSTRACT

Fostering sustainable cities necessitates a significant paradigm shift from motorised vehicles to active mobility. However, the impact of emerging transport modes like e-scooters in this transition remains unclear. To explore the potential of this shift, we polled 805 (non)users of e-scooters in Sweden via an online survey to explore (i) who are e-scooter users and (ii) how e-scooter use affects the probability of modal substitution for users. The propensity score matching method was used to obtain unbiased estimates of e-scooter usage impact on modal substitution and to construct an artificial control group, overcoming potential biases present in previous studies that exclusively surveyed e-scooter users. We found that e-scooter users are more likely to have a high-paying job, a driving license, own an e-bike and car, and public transport cards, suggesting diverse travel behaviours. These findings indicate that e-scooter users are more likely to be highly mobile people with a potential for multimodal transport. Furthermore, being an e-scooter user will increase the probability of shifting their short-range trip to an e-scooter by 46 %. Findings provide pivotal insights into e-scooter modal shifts, crucial for ex-ante and ex-post evaluations of e-scooter adoption, the deployment of e-scooter schemes, and contribute to travel demand management.

1. Introduction

Active mobility paves the way towards sustainable cities by addressing the challenges associated with motorised vehicles, such as noise and air pollution, traffic congestion, and by promoting an active lifestyle (Chibwe et al., 2021; Hosseinzadeh et al., 2021a; Lu et al., 2018; Patil et al., 2022). Active mobility primarily relies on cycling and walking; however, the challenges posed by steep terrain and long-distance travel can limit their applicability for certain trips (Abadi & Hurwitz, 2018; Kazemzadeh & Bansal, 2021a; Nikiforiadis et al., 2020). To address these limitations, powered micro-mobility options, including electric bikes (e-bikes) and electric scooters (e-scooters) have been introduced, expanding the range of active mobility choices, and overcoming challenges related to steep roads and relatively long-distance trips (Hosseinzadeh et al., 2021; Zhou et al., 2023). Hence, to enhance the role of active mobility, it becomes essential to examine the contribution of powered micro-mobility, specifically e-scooters, in the context of active transport.

The introduction of e-scooters in 2017 has led to their rapid proliferation across more than 200 cities worldwide, with estimated market values reaching billions of dollars (McKenzie, 2020; Yang et al., 2022). In 2018, e-scooters accounted for the highest proportion of micro-mobility trips in the US, with 38.5 million recorded trips (Huo et al., 2021; Younes et al., 2020). Moreover, a similar trend of increasing popularity of e-scooter usage has been observed in various European cities, further highlighting the common adoption of e-scooters as a mode of transport (Li et al., 2022). The popularity of e-scooters can be attributed to various factors, including their accessibility, relatively lax regulations, and the enjoyable experience of electrically assisted riding (Nikiforiadis et al., 2021). The rapid popularity and widespread adoption of e-scooters have presented challenges for local governments in formulating appropriate regulatory policies (McQueen & Clifton, 2022; Tuncer et al., 2020). Initially, e-scooters were viewed favourably by local governments as they appeared to promote ridership of active mobility options and alleviate traffic congestion (Weschke et al., 2022). However, issues such as traffic accidents, parking problems, and inconvenience for other road users have prompted local governments to restrict the number of operators in certain cities or implement temporary e-scooter bans (Zou et al., 2020).

The introduction of e-scooters as a new mode of transport has

* Corresponding author at: Space, Earth & Environment, Chalmers University of Technology, Gothenburg 412 96, Sweden.
E-mail address: khashayar.kazemzadeh@chalmers.se (K. Kazemzadeh).

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significant implications for urban policies and infrastructure management (McKenzie, 2019). The utilisation of sidewalks and bike lanes by e-scooters impacts the capacity and configuration of the built environment (Nikiforiadis & Basbas, 2019).The coexistence of various transport modes with different speeds and navigation characteristics can affect the safety and comfort of all road users, particularly vulnerable road users (Kazemzadeh & Bansal, 2021b). Additionally, e-scooters can influence users' short- and long-term choices of transport modes, which in turn may impact supply-demand management. Consequently, the introduction of e-scooters can be regarded as an intervention, and it is crucial to assess the impact of their deployment to inform realistic planning and regulatory measures. By evaluating the characteristics of e-scooter users and non-users and assessing the impact of shared e-scooter systems on modal substitution, this study aims to provide valuable insights into user behaviour and the potential of e-scooters as an active transport option, contributing to a better understanding of the role they play in shaping urban mobility patterns and informing future policies.

1.1. *Novelty and scope of the paper*

The existing literature on e-scooter mode choice has made substantial progress in understanding various characteristics of e-scooter adoption. However, there remains a notable gap in understanding the extent to which e-scooters act as a modal substitution for different modes of transport. This gap limits the ability to accurately evaluate the impact of e-scooter usage on modal shift. This section briefly presents the novelty and the contributions of this study to the body of the literature.

1.1.1. *Methodological advancement*

We introduce a methodological advancement by incorporating a control group and applying a rigorous methodology to estimate the modal shift to e-scooters. By including both e-scooter users and non-users in our analysis, we aim to comprehensively capture and compare their modal shift behaviours. This innovative approach enables us to discern the distinct impact of e-scooter usage on modal substitution while accounting for the demographic factors, travel habits (including the record of users' trips), and other relevant factors that differentiate these groups. To achieve this, we employ the Propensity Score Matching method to generate an artificial control group. This technique allows us to effectively control for confounding variables and obtain more precise estimates of the impact of e-scooter usage on modal substitution.

1.1.2. *First-hand evidence of e-scooter modal shift in Sweden*

Our study introduces new evidence by focusing on e-scooter usage in the Nordic context, particularly in Sweden. To the best of the authors' knowledge, this is the first study in the Northern European region explicitly evaluating the modal shift by e-scooters. We identify that cultural, social, and economic factors specific to this context may significantly influence modal choices, and our research aims to shed light on these dynamics. This is particularly important as the Nordic context has specific conditions unique even from other Western countries. Considering the popularity of e-scooters, there is a need for studies to understand the modal shift of e-scooters to assess their long-term impact and adoption.

1.1.3. *Quantifying the impact of adopting an emerging mode on modal shift*

While several studies have identified distinct demographic characteristics of e-scooter users, such as being predominantly young, male, and having higher incomes, few studies delicately analyse the impact of adopting a new mode of transport on a user's modal shift decision. Our study seeks to contribute to this understudied aspect by examining how factors such as demographics, and travel habits influence modal choices and shifts. Moreover, we include new variables such as different configurations of household structure (including dependents of different ages), various categories of trip duration, and types of modes used to access public transport. These additions provide a more comprehensive and nuanced picture of the modal shift for e-scooters.

In summary, our research advances the understanding of e-scooter modal choice by adopting a robust methodology, exploring e-scooter modal shift within a unique Nordic context, and scrutinising the impact of adopting this emerging mode on users' modal shift decisions. These contributions collectively enhance our understanding of e-scooter adoption's dynamics and its role in reshaping urban transport. In a nutshell, our research addresses two main research questions: i) What variables (e.g., socio-demographic characteristics and travel habits) describe the probability of being an e-scooter user? ii) How could being an e-scooter user affect users' probability of modal shift to an e-scooter?

The rest of the paper is organised as follows: Section 2 provides an overview of the contextual literature. Section 3 presents data and the adopted method for this study. Results and discussions (Section 4) are in the penultimate section, and the conclusion (Section 5) ensues.

2. Literature review

In this section, we briefly discuss previous studies concerning 2.1) e-scooter usage characteristics, 2.2) the impact of e-scooters on modal shift, 2.3) the usage of e-scooters in Sweden, and 2.4) knowledge gaps and research needs. For a more comprehensive review of modal shift in e-scooters, we recommend referring to recent literature review studies conducted by Wang et al. (2022) and (Kazemzadeh & Sprei, 2022). For further literature regarding current issues related to e-scooters, we recommend referring to the following review studies: Boglietti et al. (2021), providing insights into e-micromobility; O'Hern and Estgfaeller (2020), a scientometric review of e-micromobility; Şengül and Mostofi (2021), which explores sustainability aspects of e-micromobility; and Zhang et al. (2023), which examines the interaction between pedestrians and micromobility.

2.1. *E-scooter usage characteristics*

The literature regarding e-scooters has rapidly increased since 2017, and several characteristics of this mode have been assessed (Hawa et al., 2021; Hosseinzadeh et al., 2021b). Understanding the usage pattern of e-scooters via assessing their trajectory (also open-source databases) is a dominant strand of e-scooter research (Caspi et al., 2020; Zuniga-Garcia et al., 2021). This research output sheds light on several factors, such as frequent paths, peak hours, usage distribution based on weather conditions and pick-up and drop-off locations (Almannaa et al., 2021; Noland, 2021). Moreover, the socio-demographic characteristics of e-scooter users via surveys have been frequently assessed (Laa & Leth, 2020; Mitra & Hess, 2021). Understanding the characteristics of e-scooter users and non-users contributes to better planning their travel demand (Reck et al., 2021). The overall trend of the previous literature demonstrates that male users are the dominant e-scooter riders (Aman et al., 2021; Nikiforiadis et al., 2021). Also, frequent users are mainly young adults with high levels of education (Cao et al., 2021; Laa & Leth, 2020; Reck & Axhausen, 2021). Despite the fact that previous research has examined the demographic characteristics of e-scooter users, such as gender and income, there is still a lack of knowledge about the travel habits, household structure, and travel preferences of e-scooter users (Badia & Jenelius, 2023).

2.2. *The impact of e-scooters on modal shift*

Understanding the role of e-scooters in modal supplement and substitution would contribute to supply and demand management (Nikiforiadis et al., 2023; Reck et al., 2022; Wang et al., 2022). The desired substitution scenario could be that e-scooters substitute trips conducted by private cars and consequently contribute to the sustainability agenda. However, in practice, e-scooters could also substitute and supplement cycling and walking, which are already desirable forms of transport.

E-scooters have frequently been referred to as a remedy for first-last-mile (short distance) trips; however, the literature yields mixed results: e-scooters could substitute and supplement both motorised and non-motorised transport modes (Reck & Axhausen, 2021). For instance, e-scooters are applicable for short-distance trips which supplement and substitute walking and cycling (Baek et al., 2021; Gössling, 2020). In contrast, e-scooters could also replace motorised vehicle trips such as public transport and cars in various contexts, specifically for short-distance trips and when individuals own an e-scooter (Bai & Jiao, 2020; Laa & Leth, 2020; Yan et al., 2023). In this section, we provide a few examples of how e-scooters could substitute motorised and non-motorised modes of transport. In terms of e-scooter impact on substituting motorised vehicles, Gebhardt et al. (2021) conducted a study in Germany to investigate the feasibility of e-scooters as a substitute for car trips. Their findings indicated that e-scooters have the potential to replace approximately 10–15 % of motorised personal transport. Guo and Zhang (2021) explored factors regarding e-scooters potentially replacing TNCs/taxis, which include factors such as lower cost, social and entertainment trip purposes, and households with multiple vehicles contributing to the substitution of private cars. Baek et al. (2021) claimed that there is an expectation that some town bus rides could be replaced with e-scooters, as neither mode has shown a clear advantage over the other in most instances.

In contrast, several studies explored the impact of e-scooters on the modal shift of active modes. Nikiforiadis et al. (2021) conducted a study in Greece and reported that shared e-scooters mostly replaced walking and public transport trips. Yang et al. (2021) conducted a study in Chicago and reported that the introduction of e-scooter sharing has led to a 10.2 % decrease in bike sharing ridership within the same operational area. Weschke et al. (2022) conducted a study in Germany and analysed the modal substitution of e-scooters. They reported that the majority of shared e-scooter trips replace walking.

To better understand the impact of e-scooter usage on transport mode selection, it might be necessary to use methodologies that take into consideration a broader range of user characteristics, such as their typical modes of transport, household composition, and their mobility patterns. Table 1 summarises previous research regarding the modal substitution of e-scooters.

2.3. The usage of e-scooter in Sweden

Shared e-scooters were first introduced in a few cities in Sweden in August 2018 and quickly spread throughout the country by September 2019, with the support of 10 active operators (DN, 2020). However, the number of e-scooter operators in Sweden has fluctuated since then, particularly during the COVID-19 pandemic. For example, in Stockholm, only two e-scooter operators (Tier and Voi) remained active in May 2020 during the outbreak of COVID-19, and the rest withdrew their operations (Stigson et al., 2021). In Sweden, e-scooters are classified as bikes, and as a result, the rules that apply to bikes also apply to e-scooters. For example, users under the age of 15 are required to wear a helmet while using an e-scooter, and the operating speed of an e-scooter is limited to 20 km/h (Kazemzadeh et al., 2023).

The rapid popularity of e-scooters in Sweden has led to an increase in traffic safety issues. The first fatal accident involving an e-scooter occurred in May 2019, and there has been an increasing trend of accidents since the introduction of e-scooters (Stigson et al., 2021). Furthermore, e-scooters have caused several issues for other active mobility users in Sweden, such as improper parking on sidewalks and pedestrian threats. Additionally, there is a lack of information about the characteristics of e-scooter users, the impacts of modal substitution, and how providing shared e-scooter service may affect modal choice in Sweden. Such issues regarding the practice of e-scooters call for comprehensive research to evaluate the impact of e-scooter programs in Sweden.

2.4. Knowledge gaps and research needs

The literature has developed to understand the role of e-scooters in modal substitution and supplementation. However, several significant research gaps remain to be filled. First, there is a lack of research evaluating the impact of being a user of a new transport mode, such as e-scooters, on the decision of users to shift their current mode (the treatment impact on treated). This strand of research is vital in the supply and demand management of the transport sector. Second, from the methodological standpoint, there is a scarcity of research that has designed a "control group" in their study framework, which contributes to the

Table 1
Summary of previous studies regarding e-scooter modal substitution.

Author(s) (Year)	Location	Data/collection	Data analysis	Main conclusions or recommendations
Caspi et al. (2020)	The USA	Open-source databases	Descriptive statistics & spatial econometrics	E-scooters could replace some leisure trips, and they could reduce car usage
Laa and Leth (2020)	Austria	Survey	Descriptive statistics	E-scooter mainly substitute walking and public transport, and e-scooter owners demonstrate the shift from personal cars
Kopplin, Brand and Reichenberger (2021)	Germany	Survey	Structural equation modelling	E-scooters mainly substitute walking rather than other transport modes
Baek et al. (2021)	Korea	Stated preference experiment	Logit models	It could be expected that e-scooters substitute some town bus trips
Bai et al. (2021)	The USA	Open-source databases	Difference-in-Differences regression modelling	Scooter use was minor in terms of overall leisure activity growth in Austin, Texas
Guo and Zhang (2021)	The USA	Survey	Mixed logit model	E-scooters could potentially compete with the taxi, lower cost, and leisure trip purposes
Lee et al. (2021)	The USA	Open-source databases (survey)	Regression model	E-scooters could substitute several modes, including carpool, bike, and taxi trips
Fearnley (2022)	Norway	Web survey	Regression	E-scooters could be a reliable substitution for walking during the daytime
Gebhardt et al. (2022)	Germany	German national household travel survey	Descriptive statistics	E-scooters could replace 13 % of the daily car trips
Weschke et al. (2022)	Germany	Survey	Multinomial logit model	Shared e-scooter trips primarily replace walking, followed by public transport, and equally replace private bikes and cars
Asensio et al. (2022)	The USA	Natural experiment	Difference-in-Differences	Drivers face substantial increases in traffic congestion when scooters and e-bikes are banned, as many users return to passenger automobiles for last-mile travel
Luo et al. (2021)	The USA	Trip records	Difference-in-Differences	Approximately 27 % of e-scooter trips could supplement the bus system
Yang et al. (2021)	The USA	Trip records	Difference-in-Differences	The implementation of e-scooter sharing led to a 10.2 % decrease in bike sharing usage
Ziedan et al. (2021)	The USA	Infrastructure- and trip-based measures	Fixed effects regression	During an average weekday, utilitarian e-scooter trips correlate with a 0.94 % decline in bus ridership

internal validity of the research. Third, regardless of the rapid adoption of e-scooters in Northern European countries, research lags far behind the practice in evaluating the usage of e-scooters. Fourth, research is scarce on the characteristics of e-scooter users, including how active and mobile they are and their frequent transport modes, which help to predict whether e-scooters could replace cars or bikes. This study contributes to the body of the literature by exploring the impact of using e-scooters on modal shift, aiding authorities and planners in deploying new e-scooter schemes and regulating the current system. Moreover, this research is the first to provide information about both e-scooter users and non-users in the two largest Swedish cities, which have applications both internationally and in Nordic countries.

3. Methodology

The adopted methodology seeks to understand two related research questions:

RQ1) What variables (e.g., socio-demographic characteristics and travel habits) describe the probability of being an e-scooter user?
RQ2) How could being an e-scooter user affect users' probability of modal shift to an e-scooter?

The following sections present the methodology adopted to answer the research questions.

Fig. 1 illustrates the workflow of our study using the Propensity Score Matching method. It begins with collecting survey data (the blue box). The yellow boxes represent the primary step of the modelling. In this step, a logistic regression is conducted to estimate propensity scores for each individual, representing their probability of receiving a treatment based on observed covariates. After ensuring an overlap in propensity scores between treated and untreated groups (i.e., users and non-users), the matching algorithm pairs them. The matched groups are then tested for balance in observed covariates. Finally, with the balanced dataset, the impact of using an e-scooter on modal shift is estimated (the green box).

3.1. Data collection

To elicit the preference of Swedish residents regarding using e-scooters, a stated-preference study was conducted. Based on an online survey, the respondents were asked about their socio-demographic characterises, travel history and habits, and potential preferences to replace their transport mode with an e-scooter. We created the survey by using the web-based Qualtrics platform, and a pilot survey was administered to 10 % of the intended sample to identify and address any potential issues with survey questions and technical aspects. Participants in the survey voluntarily joined Dynata's respondent panels and received incentives from Dynata (a professional survey firm). The research team ensured complete separation from the recruitment process and had no contact with the respondents. The survey description provided clear instructions for participants to contact the panellist for any issues, ensuring a smooth data collection process. The survey was distributed via Dynata in April 2022 on several survey panels in the two largest cities of Sweden, i.e., Stockholm and Gothenburg. We considered April for data collection as the weather is suitable for using an e-scooter in Sweden. Therefore, participants have fresh experience and memory regarding e-scooter usage.

The survey was written in Swedish and distributed to residents of Stockholm and Gothenburg aged 16 and over. 16 is the legal age threshold in Sweden to use e-scooters. We designed the survey with three blocks to capture participants' socio-demographic characteristics, travel history and habits, and modal substitution attitudes. To identify shared e-scooter users in the survey, we designed two questions in different sections. In doing so, we asked users if they had experience using e-scooters (Question 1) and if they had used e-scooters several times per day to never (Question 2) over the past few weeks.

We converted Question 2 into a binary response where 1 represents if the person uses e-scooters several times per day and 0 otherwise. If a person positively answered these two questions (responded 1 in

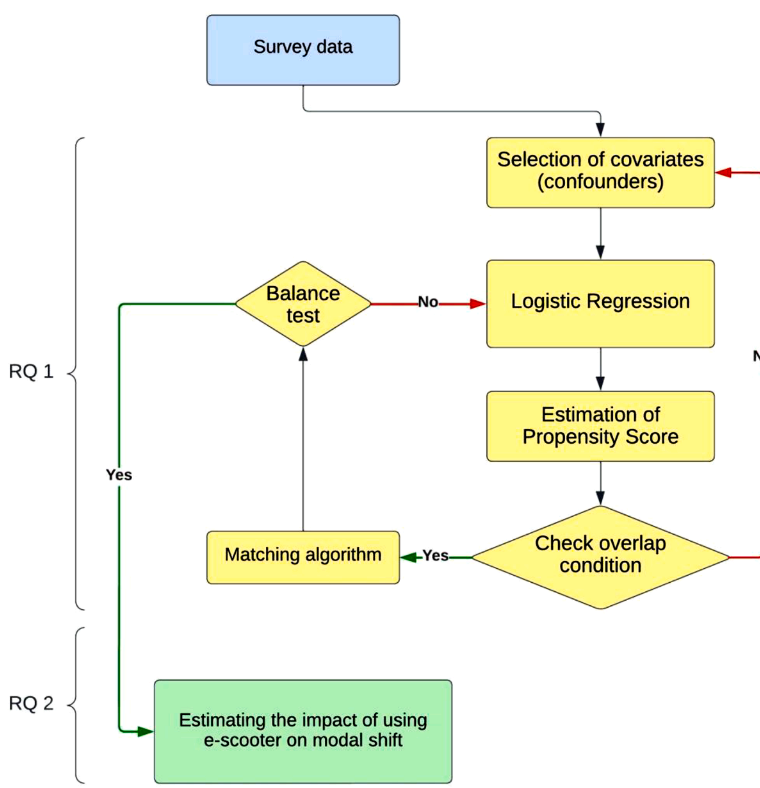

Fig. 1. The adopted methodology framework in this study (based on the Propensity Score Matching method).

Question 2), we categorised them as a user. After matching the responses of participants from these two questions, we removed the record of those participants who contradicted these two questions. We also followed the General Data Protection Regulation (GDPR) to protect and handle personal data, and the data were securely stored in an anonymised format, with each participant assigned a unique user ID that was arbitrarily defined.

The data collection process took about one month, within April 2022. In total, 1806 responses were received. We considered several checkpoints to assess the quality of the data. First, we removed the participants' records who answered the survey fast (i.e., faster than 150 s). The estimated completion time for this stated-preference survey was approximately 600 s. While we envisioned that participants would take about 600 s to complete the survey, we did not set any time limits to allow participants to respond without time pressure. Next, we designed questions to capture contradictory responses. For instance, if a participant positively answered about having experience with e-scooters in one question, they could not answer that they had never ridden e-scooters in another question. Moreover, we did not interpolate missing values for any questions and therefore removed the record of participants with even one missing value. After cleaning data, 805 records met the criteria to be included in data analysis. Table 2 presents the included variables from the survey. Our sample exhibits some biases in terms of participants' demographic characteristics. Specifically, as can be seen from Table 2, we have observed a higher proportion of female participants and individuals with current employment status. While this type of skew is not atypical in survey-based studies, it is crucial to recognise its potential impact on the results of the PMS analysis. We have detailed the breakdown of study variables categorised into user and non-user groups in Table A.1, available in the Appendix. It should be noted that the survey also had questions regarding parking issues and trip comfort, which are excluded from this study.

3.2. Propensity score matching method

To accurately analyse how an intervention or program (treatment) could influence a system, it is critical to examine the performance of the same system if the intervention had not been introduced, the so-called "control group". Randomised control trial experiments are studies in which the control group is drawn randomly from the sample, and thus potential selection bias is eliminated. These methods are powerful; however, they might be less practical to implement in some types of transport studies, such as traffic safety, vehicle membership, carsharing and travel demand (Ding et al., 2021; fka Andersson et al., 2021; Zhang et al., 2021).

In this study, we aim to understand how being an e-scooter user could affect the modal shift of users. We used propensity score matching (PSM) to estimate this effect. The PSM method has been frequently applied in similar transport domains, such as the impact of carsharing on travel behaviour (Mishra et al., 2015), bike highway on the usage of bike hire (Li et al., 2018), to estimate the causal impact of intervention/-treatment on the outcome.

The probability of treatment assignment based on observed baseline characteristics is known as the propensity score (Austin, 2011). The PSM technique uses a single index (propensity score) to build a counterfactual control group based on several matching covariates. The difference in average modal substitution (Y) between e-scooter users (SU=1) and e-scooter non-users (SU=0) can be specified as Eq. (1):

$$\begin{aligned}\Delta_{\mu} &= E\left[Y_{1,i}\middle|SU_i=1\right]-E\left[Y_{0,i}\middle|SU_i=0\right]\\ &= E\left[Y_{1,i}\middle|SU_i=1\right]-E\left[Y_{0,i}\middle|SU_i=1\right]+\ E\left[Y_{0,i}\middle|SU_i=1\right]-E\left[Y_{0,i}\middle|SU_i=0\right]\end{aligned} \tag{1}$$

Eq. (1) can be decomposed into two parts. The first part represents the causal effect, and the latter represents a selection bias. Let's consider i as several units of study, where $i = 1, 2, \ldots$ and N (i.e., individual members). The first two terms of this equation (second line) represent the average causal effect of being an e-scooter user ($SU_i = 1$). In other words, this shows the expected difference between the observed outcome ($Y_{1,i}$) and a counterfactual outcome ($Y_{0,i}$), if the users were not users. More specifically, the first two terms describe the average treatment effect on the treated (ATT). The last two terms show the self-selection bias as the expected difference between the counterfactual outcome of users if they were not users ($Y_{0,i}|SU_i = 1$), and the observed outcome of non-users ($Y_{0,i}|SU_i = 0$).

To implement the PSM, we followed three steps:

3.2.1. Prediction of the propensity score

This step is dedicated to estimating propensity scores, which could be implemented via different categories of discrete choice models. In other words, this step estimates the probability of an individual being an e-scooter user conditional on the baseline of confounding covariates. In doing so, a logistic regression model with a linear model function is adopted (Eq. (2)).

Table 2
Summary of variables included in the survey.

Variable	Description	Percentage of indicator
Socio-demographic factors		
Gender	Female indicator (1 if the respondent is a female, 0 otherwise)	58 %
Age	Year Ave: 44; Min: 16; Max: 88	
Household structure	Having children between the age of 7–12 in the household (1 if the respondent answers "Yes", 0 otherwise)	20 %
	Having teenage between the age of 13–17 in the household (1 if the respondent answers "Yes", 0 otherwise)	18 %
Job	Having a job (1 if the respondent answers "Yes", 0 otherwise)	64 %
Income	High salary job* (1 if the respondent answers "Yes", 0 otherwise) *The threshold is 30,000 SEK -Swedish Kroner	40 %
Travel history/habit factors		
E-bike owners	Having an e-bike in the household (1 if the respondent answers "Yes", 0 otherwise)	21 %
Personal car owners	Having a car in the household (1 if the respondent answers "Yes", 0 otherwise)	63 %
Work trips by bikes	Using a bike for work trips (1 if the respondent answers "Yes", 0 otherwise)	29 %
Work trips by cars	Using a car for work trips (1 if the respondent answers "Yes", 0 otherwise)	40 %
Bike as a frequent transport mode	Using a bike more than several times per day for all types of trip purposes (1 if the respondent answers "Yes", 0 otherwise)	50 %
Car as a frequent transport mode	Using a car more than several times per day for all types of trip purposes (1 if the respondent answers "Yes", 0 otherwise)	65 %
Duration of work trips	More than 30 min indicator (1 if the respondent answers "Yes", 0 otherwise)	47 %
Duration of leisure trips	More than 30 min indicator (1 if the respondent answers "Yes", 0 otherwise)	30 %
Accessing to public transport	Accessing to public transport by walking and/or cycling (1 if the respondent answers "Yes", 0 otherwise)	91 %
Driving licence	Having a driving licence (1 if the respondent answers "Yes", 0 otherwise)	74 %
Public transport monthly card	Having a monthly card indicator (1 if the respondent answers "Yes", 0 otherwise)	50 %
E-scooter monthly card	Having a monthly card indicator (1 if the respondent answers "Yes", 0 otherwise)	13 %

$$e(X_i) = P\left(SU_i = 1 | X_i = x^{\{c\}}\right) = P_i$$
$$\log\left[\frac{P_i}{1 - P_i}\right] = \alpha + \beta x^{\{c\}} i = 1, 2, \ldots, N \tag{2}$$

where $e(X_i)$ is the propensity score obtained by regressing SU_i on confounding factors specified by X_i. Also, β is the vector of regression coefficients concerning the confounding factor vector $x^{\{c\}}$, and α is the intercept.

3.2.2. Matching

Each unit of the treatment group should be paired with a similar one in the control group according to their propensity score value. Several matching methods, such as K-nearest neighbours matching, subclassification matching, calliper and radius matching, and kernel could be applied for matching. We used calliper and nearest neighbour matching methods and selected the nearest neighbour that yielded the most discrepancy between the mean of the confounding factors. These matching methods have demonstrated their success in previous transport-related studies (Xiao et al., 2023; Zhang et al., 2021).

3.2.3. Estimation of treatment effect

In the last step, the effect of treatment (being an e-scooter user) is estimated by evaluating the treatment and matched control units. This represents how being an e-scooter user could affect users' modal substitution probability.

We wrote our code in Python programming language for restructuring and cleaning data and used the Psmatch2 package in STATA to implement the PSM method (Leuven & Sianesi, 2003).

To obtain valid causal inference from PSM, the model needs to satisfy three main assumptions:

3.2.4. Conditional independence assumption (CIA)

The CIA represents the state that conditional on the observed confounding factors X_i, the treatment assignment should be independent of the potential outcomes. This conditional dependence can also be obtained by conditioning on a scalar rather than high-dimensional baseline covariates (Rosenbaum & Rubin, 1983). Eq. (3) represents CIA formulation.

$$SU_i \perp (Y_{0,i},\ Y_{1,i}) \big| X_i$$
$$= SU_i \perp (Y_{0,i},\ Y_{1,i}) \big|\ e(X_i) \tag{3}$$

3.2.5. Common support condition (CSC)

This assumption (also called overlap assumption) is intended to check if a control group can be detected for each treatment group. This assumption could be tested by mapping the distribution of the control group's propensity score against the treatment group's propensity score. In other words, the conditional distribution of X_i when $SU_i = 1$ should overlap the conditional distribution of X_i when $SU_i = 0$. Eq. (4) specifies CSC:

$$0 < P(\ SU_i = 1 | X_i) < 1 \ including\ all\ x \tag{4}$$

3.2.6. Stable unit treatment value assumption (SUTVA)

The main requirement to satisfy SUTVA is that each unit's outcome must be independent of how other units are being treated (Graham et al., 2014).

4. Results and discussion

In this section, we provide the results and discuss them within the body of literature. In this section, we briefly discuss 4.1); propensity score model; 4.2) matching results; 4.3) impact of the e-scooter program on modal substitution; and 4.4) finding's implications.

4.1. Propensity score model

To estimate the model, three variables from the survey: having a job, the primary transport mode, and how they get to public transport were used in the logistic regression. The selection of these specific variables—job status, primary mode of transport, and access to public transport—was made with careful consideration of their unique potential impact on modal shifts to e-scooters. The presence or absence of a job was chosen as it serves as a critical demographic characteristic that has been consistently highlighted in the existing literature on transport user behaviour, particularly in the context of e-scooters (Kazemzadeh & Sprei, 2022). The inclusion of participants' primary mode of transport aligns with our main research objective, which is to understand modal shifts to e-scooters based on their initial transport choices. Additionally, the consideration of accessibility to public transport was motivated by the central role e-scooters often play in addressing short-distance travel needs and connecting with other modes of transport for longer trips, commonly referred to as "first-last-mile" solutions. Each of these variables presents unique participant characteristics that provide valuable insights into their decisions regarding modal shifts and serve as a solid foundation for our modelling. Subsequently, we iteratively added one covariate at a time and checked the likelihood ratio test to decide if the variable should be included in the model specification. The primary purpose of the propensity score model is to build an index to reflect all confounding factors, not to predict treatment assignment. Table 3 presents the estimation results of the logistic regression model. This section briefly discusses the multivariate correlations obtained in this model. The coefficients indicate that e-scooter users are less likely to be female, old, and have teenage dependents in their household. On the other hand, e-scooter users are more likely to have jobs with high salaries and children between 7 and 12 in their household.

When it comes to vehicle holdings, we find statistically significant effects of having an e-bike and car in the household of e-scooter users. It is also likely that they use their cars frequently (more than several times per day). The connection with car usage is also reflected in the fact that e-scooter users are likely to have a driving licence. For other modes of transport, we find that they are less likely to be frequent bike users, and to walk or cycle to get to public transport. Plus, it is more likely that e-scooter users have monthly access cards for both e-scooters and public

Table 3
Summary of results of propensity score model (logistic regression model).

Confounders	Coef.	SE
Intercept	2.576***	0.199
Gender	−0.381***	0.075
Age	−0.071**	0.002
Children dependent (between 7 and 12)	0.203**	0.095
Teenage dependents (between13 to 17)	−0.608***	0.105
Job	0.488***	0.088
Income	0.609***	0.081
E-bike owners	0.769***	0.102
Personal car owners	0.280***	0.080
Work trips by bikes	0.175*	0.153
Work trips by cars	−0.405*	0.238
Bikes as a frequent transport	−0.342***	0.099
Car as a frequent transport	0.158**	0.084
Duration of work trips	−0.216***	0.035
Duration of leisure trips	−0.078**	0.038
Accessing to public transport	−0.110***	0.033
Driving licence	0.618***	0.094
Public transport monthly card	0.323***	0.075
E-scooter monthly card	0.486***	0.139
McFadden's pseudo R-squared	0.285	n.a.

Note:
* $p < 0.1$;.
** $p < 0.05$;.
*** $p < 0.01$;
n.a.: not applicable.

transport. The average overall trip duration of e-scooter users is shorter than 30 min.

4.2. Matching results

Prior to using the estimated propensity score for matching, we examine the "common support" condition. This is the second assumption of the PSM method, discussed in *3.2 Propensity score matching method*. The propensity score distributions for both e-scooter users and non-users are shown in Fig. 2. The histogram demonstrates the treatment and control groups overlap for all score ranges. This confirms that there is no treated unit outside the region of common support; thus, no observations must be discarded. Consequently, we infer that the overlap assumption is viable in our empirical analysis. This testing method has been frequently applied in previous studies in the transport domain Ding et al. (2021), Li et al. (2018), Zhang et al. (2021).

Following the matching step, the PSM technique attempts to balance the distribution of confounders between the e-scooter users and non-users' groups (treatment and control groups, respectively). To further inspect the quality of matching, we performed the balance test for calliper and nearest neighbour matching methods. We exclude the result table for brevity, but the parameter estimates show the improved overall balance of all confounding factors.

4.3. The impact of the e-scooters on modal substitution

In this section, we estimate the impact of using e-scooters on modal substitution for short distance trips (less than 4 km). In other words, we explore how being an e-scooter user could increase/decrease the probability of modal shift – the so-called effect of treatment on treated. We asked respondents about the probability of shifting to e-scooters from their frequent mode (i.e., very likely, moderately likely and less likely). We combined the positive responses (i.e., very likely and moderately likely) versus the negative ones (less likely) and built a binary response. In the binary response, 1 represents the inclination towards shifting to use an e-scooter and 0 otherwise.

Within our study's sample, 49 % of participants identified as frequent e-scooter users. Furthermore, approximately 65 % indicated using a bike several times per week, and 79 % reported using a car several times per week. The results indicate that being an e-scooter user increase 46 % the probability of a modal shift to e-scooters. Table 4 summarises the results of the average treatment in the treated group. The ATT row in Table 4 presents the comparison between e-scooter users and non-users (control) regarding the probability of modal shift. It demonstrates that e-scooter users have a higher probability of modal shift compared to non-users. To assess the magnitude of this difference in a relative sense, we consider the control probability in the ATT row as a reference point. By comparing the probability of modal shift between e-scooter users and non-users relative to this reference point, we can determine the percentage increase.

This result shows that e-scooters can impact the modal shift of users for trips under 4 km. It should be noted that this result does not directly reflect which transport modes will be directly replaced by e-scooters. Our results show that they are frequent car users, indicating that some of these trips may be replaced, but also that they are holders of monthly public transport cards, which could imply that public transport trips are replaced instead.

4.4. Finding's implications

In this section, we discuss the application of the study and map them against the existing literature. This section contains (i) e-scooter users' characteristics, (ii) the impact of using e-scooter in modal substitution, and (iii) limitations and outlook.

4.4.1. E-scooter users' characteristics

The discussion in this section is derived from the outcomes presented in Table 3, titled "Summary of results of the propensity score model (logistic regression model)". In terms of e-scooter users' socio-demographic characteristics, they are less likely to be women (−0.381) and older (−0.071). This finding is in line with the literature, as e-scooter riders are reported to be more likely male and young adults (Kazemzadeh & Sprei, 2022). Also, e-scooter users are more likely to have a job (0.488) with a high salary (0.609), which is in agreement with previous research findings (Yang et al., 2022). It is worth noting that several previous studies reported such findings based on university

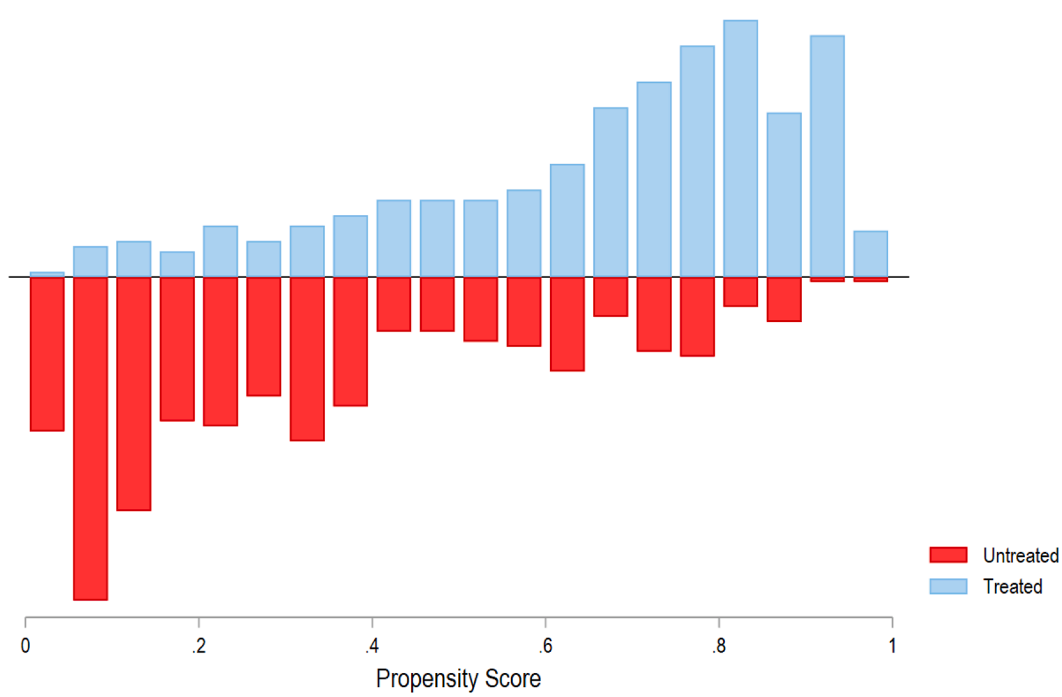

Fig. 2. Results of overlap test based on propensity score distribution.

Table 4
Results of the PSM model for the impact of the e-scooter program on modal shift.

Variable	sample	Treatment	Control	Difference	SE	T-stat	Effects (%)
Modal shift	Unmatched	0.5934	0.2192	0.3742	0.013	28.66	*46 %
	ATT	0.5934	0.4065	0.1868	0.065	2.85	

Note:.
* Statistical significance at the 5 % level.

towns, while the current study obtained similar results based on case studies in two large Swedish cities. Therefore, being male-dominant, users with a job and high salary could be expected to describe the socio-demographic characteristics of e-scooter users regardless of the size of the city. We also found that e-scooter users are less likely to have a dependent teenager (−0.608) in their household than younger children (0.203). This finding is an addition to the literature as it describes the household structure of users. Having children in the household might reinforce the need for the trips of two persons simultaneously (e.g., picking up children from school). In sum, our results give a more nuanced and richer picture of e-scooter users' socio-demographic characteristics.

Our results on vehicle ownership and general transport behaviour, i. e., that they are likely to own both cars (0.280) and e-bikes (0.769), as well as holding monthly public transport (0.323) and e-scooter (0.486) access cards, is an addition to the literature by showing that e-scooter users could be considered highly mobile people and interested in the multimodal transport system. Also, e-scooter users are more likely to use bikes (0.175) for commute trips and less likely to have work trips longer than 30 min (−0.216). Hence, our results give a mixed picture when it comes to other modes of transport. E-scooter users frequently use the car (0.158), but are more likely to own an e-bike and have a monthly public transport card.

Juxtaposing the characteristics of e-scooter users with other transport modes can provide valuable insights for policymakers and planners. First, the user of shared mobility is deemed to be a young adult, as in the case of carsharing (Becker et al., 2017; Dias et al., 2017). Second, comparing the age range of electrically assisted transport modes shows that e-bikes enable older adults to use active modes while e-scooter users are mainly younger adults (Kazemzadeh & Ronchi, 2022). This might be due to the longer history of e-bikes compared to e-scooters, the similarity of e-bikes to conventional bikes, and thus their acceptance as a transport mode amongst older adults. Also, the riding postures of these modes are different, and e-scooter riders need to stand up, which is not the case for e-bikers, which might be a barrier for older adults (Kazemzadeh, 2021). Finally, male users are overrepresented in both bike and e-scooter modes which could affect transport and gender equity (Burghard & Dütschke, 2019; Cao et al., 2021). This essential factor needs further assessment in future research, and its causes should be evaluated.

To foster a more inclusive and equitable transport system, stakeholders and planners should prioritise addressing the demographic disparities in e-scooter usage. Our research has revealed a predominant user base of young, high-income males, necessitating a shift towards a more diverse and representative rider profile. Incentive programs could play a crucial role in addressing this issue, as stakeholders and planners collaborate to design initiatives tailored to encourage underrepresented groups to use e-scooters. This could involve offering reduced pricing for older adults, or individuals from low-income backgrounds. Furthermore, enhancing infrastructure to accommodate a diverse range of riders, including older adults, could increase the appeal of this mode of transport. This could involve the improvement of dedicated active mode lanes, easily accessible parking spots, and strategic distribution of e-scooters throughout the city to meet the needs of diverse users.

4.4.2. *The impact of using e-scooter in modal substitution*

E-scooters are easily accessible, faster than conventional cycling and walking and more enjoyable to use due to the electrically assisted riding experience (Foissaud et al., 2022; Kazemzadeh & Bansal, 2021a). They can substitute and supplement existing modes, which can have an impact on the supply and demand system. Therefore, studying their impact and role in modal substitution and supplement is important to manage the supply and demand of the transport system effectively, and to provide sustainable, efficient, and safe modes of transport to the public.

To address this research need, we took two steps in this study. First, we explored the confounders to present who are e-scooter users, which is summarised in the previous section. This step is crucial as it can show how the characteristics of emerging mode users, in this case, e-scooters, differ from or are similar to other modes and thus discuss potential trip shifts. Second, based on the characteristics that described an e-scooter user, we quantified how being an e-scooter user could affect the probability of modal shift – the so-call impact of treatment on the treated. We found being an e-scooter user will positively increase the probability of shifting the frequent mode of users to an e-scooter for shorter trips. This result shows that the e-scooter program strongly impacts the modal shift decision of users toward e-scooters. It should be noted that we could not directly reason for which mode will primary will be replaced by e-scooters. Given that e-scooter users are likely to have frequent car trips, it is probable that some of these trips will be replaced by e-scooters. However, e-scooter riders are also likely to have a monthly public transport card.

Previous studies claimed mixed results for transport modes that e-scooters could replace (see 2.2 The impact of e-scooters in the modal shift for more details). Indeed, the favourable scenario is that e-scooter substitute motorised vehicles and contribute to a more environmentally friendly society (Lazer, 2023). However, supplementing conventional cycling and walking with e-scooters could also be beneficial for users as e-scooter might increase trip comfort by a faster and still active transport mode. Yet, more research is needed to evaluate how the substitution of other transport modes by e-scooter could affect the environment considering the life cycle assessment of e-scooters. This body of literature is required to guide planners and policymakers to have realistic expectations of such emerging modes' impact on the environment.

For stakeholders and planners, a comprehensive understanding of the impact of e-scooters on modal substitution is a critical component of effective transport strategy. Our research underscores the growing inclination of users to use e-scooters, a factor that carries significant implications for planners and policymakers. The potential of e-scooters to complement and potentially replace existing modes of transport raises questions regarding supply and demand management within urban transport systems.[1] To uncover the full potential of e-scooters and encourage a transition away from car trips, stakeholders and planners should develop and implement policies that facilitate this shift. By strategically placing e-scooter stations near public transport stations, potential users can easily incorporate e-scooters into their daily commute, addressing first-last-mile challenges. These measures can enhance access to public transport, reduce car dependency, and contribute to a more sustainable urban environment.

[1] https://www.numo.global/spotlight-on/micromobility/why-do-people-use-new-mobility-services-behavioral-study

4.4.3. Limitations and outlook

This research inevitably has some (de)limitations. First, we only considered the resident of the two Swedish cities (i.e., Stockholm and Gothenburg). This study is representative of a similar Nordic context; however, this might impact the generalisability and transferability of the findings in other countries. Moreover, it is essential to acknowledge that our sample exhibits some biases in terms of participants' demographic characteristics. Specifically, we have observed a higher proportion of female participants and individuals with current employment status. Since e-scooter usage is more common amongst men this could imply, e. g. that we slightly underestimate the substitution effect. Second, the survey was written in Swedish; thus, English-speaking participants were excluded. Third, we only considered participants 16 years or older who legally can rent and use e-scooters. However, the younger adult might use e-scooters, and their perspectives are excluded from this study. Fourth, a large percentage of dummy variables could restrict the benefits of a flexible spline definition of the link function.

Future research could expand the scope of this study by comparing e-scooter users in Swedish cities with those in other Nordic countries and worldwide, providing a comprehensive analysis of user characteristics. Additionally, examining the simultaneous impact of multiple shared modes of transport, such as e-bikes, on users' modal shift decisions could aid in managing travel supply and demand. To broaden the demographic representation, future studies could also consider the perspectives of younger children who may use e-scooters despite being under the age of 16. Furthermore, exploring the impact of safety concerns on e-scooter usage, which was not included in the current analysis, could shed light on essential factors influencing adoption.

5. Conclusion

This study provides a novel framework to understand the impact of e-scooter programs on modal substitution. We surveyed 805 Swedes to investigate the socio-demographics, travel history, and habits of e-scooter users and then estimate how being an e-scooter user may impact the probability of modal shift. Through PSM, we can get more robust results that take into consideration of non-users, which is not often used in the literature on e-scooters, where normally only users are surveyed. Our results give a more nuanced picture of e-scooter users. Similar to the literature, we find that being a younger man increases the probability of being an e-scooter user. However, we also find that they have a higher salary and are more likely to have kids aged 7–12 in the household. When it comes to other transport modes, we find that they are likely to have a car and e-bike and have a monthly public transport card. Trip length wise, they are more prone to have shorter trips. Thus, we can presume that e-scooter users are highly mobile people and that they are open to different transport modes. Furthermore, being an e-scooter user increases the probability of users shifting to an e-scooter by 46 % for short distance trips. The findings have applications for policymakers to understand the target demographic for e-scooter usage better, know the impact of using e-scooters on modal shift, and tailor their policies and regulations accordingly.

Declaration of Competing Interest

There are no conflicts to declare.

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Appendix

Table A.1
Distribution of users and non-users for each study variable.

Confounders	User (percentage)	Nonuser (percentage)
Gender (Female)	44 %	56 %
Age (avg)	22 %	78 %
Having children between the age of 7–12	72 %	28 %
Having children between the age of 13–17	68 %	32 %
Having a job	61 %	39 %
High salary job	58 %	42 %
Having an e-bike	71 %	29 %
Having a car	65 %	35 %
Using a bike for work trips	72 %	28 %
Using a car for work trips	66 %	34 %
Bike as a frequent transport mode	65 %	35 %
Car as a frequent transport mode	79 %	21 %
Duration of work trips more than 30 min	52 %	48 %
Duration of leisure trips more than 30 min	51 %	49 %
Accessing to public transport by walking/cycling	50 %	50 %
Having a driving licence	51 %	49 %
Public transport monthly card	57 %	43 %
E-scooter monthly card	82 %	18 %
Gender (Female)	44 %	56 %

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