E-scooter sharing to serve short-distance transit trips: A Singapore case

E-scooter sharing to serve short-distance transit trips: a Singapore Case

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Abstract: E-scooter sharing provides a last-mile solution to complement transit services, but less was known about its effectiveness in serving short-distance transit trips. We investigate the potential of using e-scooter sharing to replace short-distance transit trips of excessive indirectness, multiple transfers, and long access-egress walking. First, we conducted a stated preference survey on e-scooter users in the Central Area of Singapore and estimated mixed logit models to examine factors influencing the choice of e-scooters and transit. We then calculated the number of transit trips that can be replaced by e-scooters. Second, we analyzed the decision of e-scooter companies in terms of the trade-offs between serving more e-scooter trips and making more revenue under varying fares. The results show that fare, MRT transfer, and MRT access-egress walking distance have significantly negative impacts on mode utilities with random tastes among respondents. Male, young and high-income groups are more heterogeneous in e-scooter preferences compared with other groups. The loss of mode share can be nearly 17% if maximizing the revenue. We classify trade-off situations into five categories and provide suggestions of how to balance between mode share and revenue for each category. Several implications are drawn for better harnessing and regulating this new mobility service, including where to deploy e-scooters to satisfy the demand unmet by the transit and how to reach a proper balance between private operators and public welfare.

Keywords: E-scooter sharing; Public transit; Modal shift; Stated preference; Mixed logit models; Travel demand analysis.

1. Introduction

1.1 The emergence of e-scooter sharing as a new micro mobility service

E-scooter sharing becomes a new micro-mobility service in many cities, after various start-ups sprouted around the globe since 2017, such as Bird, Lime, Spin, and Skip in United States and Europe, Telepod and Neuron in Singapore. Some ride-hailing companies also smelled opportunities and invested in this new option, like Lyft Scooters, Jump, and GrabWheels. A typical shared e-scooter in Singapore is a two-wheel vehicle concisely designed with a standing deck and a handlebar, powered by the electric battery (Fig. 1). E-scooter-sharing service brings convenience to the public. Users can unlock e-scooters with smartphones, and pay after ending trips. E-scooter sharing companies need to recharge and rebalance periodically to maintain good services.

The e-scooter provides an environmentally-friendly alternative to other transportation options. It was perceived to reduce carbon emissions (Hwang J., 2010), improve life quality and health (Zagol B. and Krasuski R., 2010), offer mobility aid to the elderly (May E. et al., 2010; Johnson M. et al., 2013; Pettersson I. et al., 2016) and the disabled (Hoenig H. et al., 2007; Jannink M. et al., 2008; Samuelsson K. and Wressle E., 2014). Since the sharing economy in transportation swept the world from early 2010s, e-scooter sharing emerged as a new concept that enabled mass utilization of smart and affordable mobilities for short-distance trips (see the mottos of Bird[1] and Lime scooter[2]). Attentions were largely drawn to how users parked e-scooters (Fang et al., 2018), e-scooters nuisances (Riggs and Kawashima, 2020), user safety concerns (Allem and Majmundar, 2019; Badeau et al., 2019; Sikka et al., 2019; James et al., 2019), data privacy (Peterson, 2019), customer segments (Degele et al., 2018), fleet distribution optimization (Chen et al., 2018), social equity (Wood et al., 2019), and spatiotemporal usage patterns (McKenzie, 2019; McKenzie, 2020).

Fig. 1. Examples of shared e-scooters in Singapore (Neuron)

1.2 An opportunity to replace short-distance transit trips

As the e-scooter service rapidly expands, limited research was conducted to examine the impacts of e-scooter sharing on other transport means. The reports in United States revealed that the e-scooter sharing had replaced some driving in Portland (Portland Bureau of Transportation, 2019), reduced ride-hailing trips in San Francisco (Rao, 2018), and would be a strong alternative

[1] https://www.bird.co/.
[2] https://www.li.me/about-us.

to private automobiles for trips between 0.5 and 2 miles in Chicago (Smith and Schwieterman, 2019). Fitt and Curl (2019) discovered that 57% of e-scooters replaced trips that would otherwise had been made by active modes in New Zealand. However, the relationship between the e-scooter sharing and public transit was not fully explored, which is the gap that this research aims to investigate.

Our study focuses on a Singapore case. Public transport plays a significant role in facilitating daily travels in Singapore, partly due to strict car ownership regulation and congestion pricing. Specifically, the Mass Rapid Transit (MRT, i.e., metro system) reached a mode share of 28% (not including bus) in 2016 (Land Transport Authority, 2018). While MRT serves efficiently for most trips, it is inconvenient to take some short-distance MRT trips in Singapore Central Area (SCA) (shown in Fig. 2) because of excessive indirectness, multiple transfers, and long access-egress walking distance (Tripadvisor, 2018). As revealed by 2012 Singapore Household Interview Travel Survey (HITS)[3], the average MRT indirectness (ratio of MRT network distance to the shortest street path) is 1.314 for the MRT trips that started and ended in SCA, and its maximum ratio reaches 4.112, which is much more than the average indirectness of global transit networks (Derrible and Kennedy, 2010). In SCA, 20.98 % of MRT trips have at least 1 transfer which is higher than the average transfer level in Singapore, and passengers have to walk for almost 1km on average to reach MRT stations. Thus, even if the trip origins and destinations are geographically close to each other, the travelling distance and time on MRT network could turn out to be long. To provide more transport options for short-distance trips in SCA, some e-scooter sharing companies, like Neuron, launched their services in 2018. Neuron deployed e-scooters in SCA and designated the e-scooter parking locations inside a geo-fence (Fig. 2). SCA is a compact, high-density, and mixed land-use planning area for business, recreation, and culture. The new micro-mobility service may offer a competitive option to replace certain short-distance transit trips in SCA, by providing a direct connection with no transfer and less working efforts[4]. For example, it takes 30 minutes and 2 transfers for a passenger to travel from Rochor station to Bencoolen station by MRT, but only 8 minutes by a direct e-scooter at the speed of 7km/h (Appendix A). This finding is also supported by the HITS data: if taking 3km as a comfortable riding distance for e-scooters, 16.1% of the MRT trips, which are longer than 3km in transit network distance, would otherwise be served more directly with e-scooters under 3km if using the shortest street paths; the percentage increased to 23.7% if users willing to ride 3.5 km (Appendix B).

[3] Singapore Household Interview Travel Survey is a national travel survey conducted every four to five years, which is designed to capture personal characteristics and daily trip-making decisions of each person in the household.
[4] Given that the Singapore bus headway could reach up to 30 minutes during off-peak hours, we did not compare the e-scooter sharing to bus for short-distance trips.

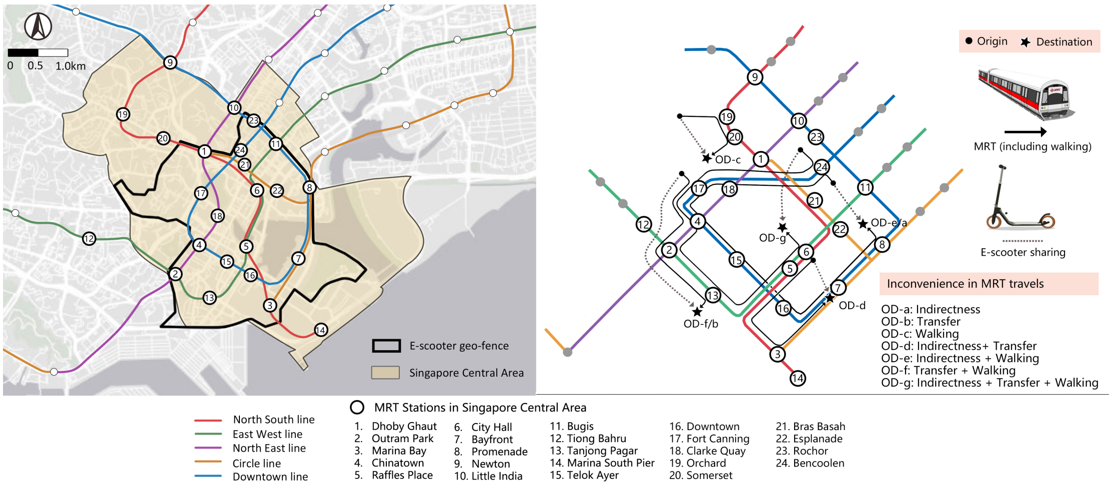

Fig. 2. MRT network in Singapore Central Area (left) and scenarios that e-scooter is competitive to MRT (right)

1.3 Research goal and questions

This study attempts to understand to what extent e-scooter sharing can replace short-distance transit trips. We approach in two facets. The first is on users' perceptional level through a stated preference survey. In other words, how people state their preferences for e-scooters over transit in different scenarios. The second is on e-scooter companies' operational level: given the users' stated preference, how would the e-scooter sharing company tradeoff between serving more trips and seeking more revenue. Three research questions (RQ) are outlined below. RQ1 and RQ2 focus on the first facet, and RQ3 is centered on the second.

RQ1: What variables and how they influence users' mode choices of e-scooter sharing and transit?

RQ2: How many short-distance transit trips are perceived to be replaced by e-scooters?

RQ3: How will e-scooter sharing company tradeoff between mode share maximization and revenue maximization?

The rest of the paper is organized as follows. Section 2 gives an overview of existing work in this domain. Section 3 explains the research methods and data processing. The results of three research questions are presented in section 4. Then a broader view of this study is discussed in section 5. Finally, section 6 summarizes our findings as the conclusion.

2. Related work: relationship between shared micro mobility and public transit

This literature review focuses on the relationship between shared micro mobility and public transit. Since e-scooter sharing literatures are limited, we also include bike sharing—a similar but more studied domain. Many studies investigated inter-modality between shared micro mobility and transit. Shaheen S. and Chan N (2016) reviewed the history of shared mobility and underlined that shared bikes and e-scooters were potentially playing a pivotal role in promoting multimodality by serving first and last mile trips. Shaheen S. and Cohen A. (2018) reviewed the convergence of trends leading to fundamental changes in public transportation, and highlighted the potentials of shared micro mobility as last-mile connectors to transit. Wisniewski (2018) found that scooters could fill gap in Chicago for short trips to and from transit. Jin F. et al. (2018) studied the dockless shared-bikes in Beijing and revealed that increases in shared-bike rides lead to increases in subway traffic, attributing it to the complementary effect of bike sharing on subway. Zhang Z et al. (2018) mapped the bicycle traffic on an equal population cartogram of Shanghai and demonstrated that the bicycle-metro integration had already become a basic model for daily transport in Shanghai. Zhou et al. (2018) carried out questionnaires on modal shift in metro commuting of Shanghai and revealed that one third of respondents shifted from walking and feeder bus to dockless bike in connecting metro commuting. Campbell et al. (2016) investigated the role of shared bikes and e-bikeshare as an attractive first and last-mile solution, determining that e-bikeshare drew users from bus links but it was unclear for shared bikes. U.S. Department of Transportation (2018) set the goal of improving regional performance by integrating shared mobility into multimodal transportation. All these researches demonstrated that shared micro mobility could provide first and last-mile connections to public transit as a complement, but did less to investigate its substitutional or replacing impact on transit trips.

Shared micro mobility is competitive to serve short-distance trips, especially when it is more direct than public transports, more affordable than automobiles, and more effort-saving than walking. McKenzie (2020) revealed that e-scooter services had been established based on an induced demand for short-distance travel options in Washington D.C. Smith and Schwieterman (2019) analyzed hypothetical trips in Chicago and found that e-scooter was an attractive option for short trips, but less important for the long haul. Limited studies investigated how shared micro mobility would replace other transport services for short-distance trips. Some compared the duration of shared micro mobility with ride-hailing (McKenzie, 2020) and taxi (Faghih-Imani et al., 2017) and suggested that shared bike and e-scooters would be a competitive alternative to automobiles for short trips during peak hours. Fitt and Curl (2019) designed a survey and revealed that e-scooter users were most likely to use e-scooters in substituting walking, private cars, and ride sourcing for short trips around 3km. But to the best of our knowledge, to what extent the shared micro mobility would replace public transit for short-distance trips was not explored.

3. Methods and Data

The methods and data processing in this paper comprise four steps. First, we measure the transit network indirectness, transfer, and access-egress walking. Second, we did a stated preference survey to Neuron e-scooter users and structured the survey to make e-scooters and MRT as competitors for short-distance trips. Third, based on the stated preference survey, we develop mixed logit models to examine factors influencing the choice of e-scooters and MRT (RQ1). Fourth, we use the observed Neuron e-scooter trips as a proxy of short-distance travel demand. Based on the estimates of logit models, we calculate the potential of using e-scooters to serve transit trips at different levels of indirectness, transfer, and walking (RQ2). In the end, we measure the trade-offs between e-scooter mode share maximization and revenue maximization under a dynamic pricing (RQ3).

3.1 Measuring transit network indirectness, transfer, and access-egress walking

Transit designed for general public will inevitably lead to inconvenience for individuals due to indirect route, transfers (Metropolitan Transportation Authority, 2019), insufficient coverage ratio (AllTransit, 2019), last-mile gap (Government Technology, 2017), and long headway or waiting time (Jiao and Dillivan, 2013), etc. Given the characteristics of SCA, we measure the inconvenience of short-distance transit trips by MRT network indirectness (I_m), MRT transfer

(R_m), and MRT access-egress walking distance (W_m).

Transit networks designed for a large spatial coverage will result in indirectness (Black, 1995; Murray et al., 1998; Kepaptsoglou and Karlaftis, 2009). Levinson and EI-Geneidy (2009), Barthelemy (2011), Huang and Levinson (2015) defined the transit network indirectness as the ratio of the shortest network distance over the Euclidean distance between origins and destinations. Zhao and Ubaka (2004), Zhao (2006), Zhao and Zeng (2006) measured the transit route indirectness as the ratio of the distance along the transit route over the shortest street network distance between two nodes with a weighting factor. Lee (2006 and 2012) defined the transit network indirectness as not only an absolute degree of circuity (difference between the travelling time on a current transit network and on a hypothetical transit network of the possible shortest connections), but also as a comparative degree of competitiveness (difference between auto and transit travel time). Research revealed that transit network indirectness would reduce transit ridership (Huang and Levinson, 2015; Lee, 2006). Moreover, transit transfer would make a trip more onerous by incurring additional travelling time and physical activities (Horowitz and Zlosel, 1981; Guo and Wilson, 2004). Transfer was estimated to generate penalties equivalent to 4.9 minutes of in-vehicle time in London (Guo and Wilson, 2011) and 5 to 15 minutes of in-vehicle time in general (Litman, 2008). Derrible and Kennedy (2010) compared the transit network structures of 33 cities, and pointed out that Singapore had a high transfer possibility and a large number of the maximum transfers. Reducing transit transfers has been proposed as an important goal for transit network optimization (Zhao and Ubaka, 2004; Zhao, 2006; Zhao and Zeng, 2006; Yu et al., 2012). Additionally, increasing the coverage ratio to reduce access-egress walking distance is crucial for enhancing transit service quality (Guihaire and Hao, 2008). Research showed that longer walking distance to transit station would decrease transit ridership (Keijer and Rietveld, 2000; Zhao et al., 2003; Derrible and Kennedy, 2009).

In this study, the MRT network indirectness (I_m) is measured as the ratio of the travelling distance using MRT network (including MRT access-egress walking distance) over the shortest path on street network. The access-egress walking distance (W_m) is measured by sum of the first and last-mile walking distances following the shortest path on street network. The shortest path is calculated using Dijkstra's algorithm (Dijkstra, 1959).

3.2 Stated preference survey

We carried out a stated preference survey to Neuron e-scooter users and asked them about choices of e-scooters or MRT under a series of scenarios, based on which to estimate the coefficients of variables influencing users' mode choices using logit models.

First, considering the indirectness, transfer, and access-egress walking distance in transit trips, we selected the following variables to define the scenarios in the stated preference survey: number of MRT stop (S_m), number of MRT transfer (R_m), MRT access-egress walking distance (W_m), MRT fare (F_m), MRT traveling time (T_m), e-scooter travelling time (T_{es}), and e-scooter fare (F_{es}). The e-scooter fare was set by the Neuron e-scooter company at the rate of 1 SGD (Singapore dollar) to start and 0.12 SGD per minute after the first minute. For calculating the MRT travelling time, we did a field survey and observed that pedestrians in Singapore central area usually walked at an average speed of 3km/h and spent about 6 minutes to enter the starting MRT station and exit the ending MRT station, 2.5 minutes to pass one MRT stop, and 3 minutes to take one MRT transfer. Thus, in the stated preference survey we assumed that MRT traveling time was calculated as W_m * (20 minute/km) + S_m * 2.5 minute + 6 minute + R_m * 3 minute.

Then, we set the variables at multiple levels to construct the experiment (Table 1). There are 24 MRT stations near Neuron e-scooter parking locations in SCA. MRT trips in SCA are often short, and the majority of them have no more than 6 stops and 2 transfers[5]. Our field survey revealed that passengers normally walked less than 0.8 km to reach a single MRT station. Based on the range of these MRT variables, we categorized the number of MRT stop with three levels (2, 4, 6), the number of MRT transfer with 3 levels (0, 1, 2), and the MRT access-egress walking distance with 2 levels (0.6 km, 1.2 km). The variable MRT fare was set based on the official MRT fare calculator, which normally cost 0.77 SGD for 1-2 stops, 0.97 SGD for 3-4 stops, and 1.07 SGD for 5-6 stops. Also, as revealed in the summary of Neuron users' traveling distances (Appendix C) and the relation of traveling time and distance (Appendix D), 70.22% e-scooter trips were shorter than 3 km, which took about 10 minutes for 1 km, 20 minutes for 2 km, and 30 minutes for 3 km. Therefore, we grouped the e-scooter travelling time into three levels (10 minutes, 20 minutes, 30 minutes), with the corresponding e-scooter fare as 2.08 SGD, 3.28 SGD, and 4.48 SGD.

[5] Only the trips from Marina South Pier MRT station to Newton MRT station have 7 stops, and only the trips from Bugis MRT station to Bencoolen MRT station have 3 transfers.

Table 1. Setting the levels of variables in the stated preference survey

Variables	Levels
MRT stop (S_m)	2, 4, 6
MRT transfer (R_m)	0, 1, 2
MRT access-egress walking distance (W_m)	0.6 km, 1.2 km
MRT fare (F_m)	0.77 SGD for 1-2 stops 0.97 SGD for 3-4 stops 1.07 SGD for 5-6 stops
MRT travelling time (T_m)	W_m * (20 minute/km) + S_m * 2.5 minute + 6 minute + R_m * 3 minute
E-scooter travelling time (T_{es})	10 minutes 20 minutes 30 minutes
E-scooter fare (F_{es})	$1 + 0.12 * (T_{es} - 1)$

Next, by combining three levels of MRT stops, three levels of MRT transfers, two levels of MRT walking distance, and three levels of e-scooter time/fare, we obtained 3*3*2*3=54 scenarios. We removed impossible combinations and finally generated 34 scenarios to carry out an online stated preference survey. The impossible scenarios include the situations where alternative e-scooter travelling time is unrealistically long or short and the situations where the number of MRT transfers is equal to or more than the number of MRT stops. Since it was not ideal for one respondent to answer 34 questions, we divided 34 scenarios into 5 questionnaire groups shown in Appendix E. Respondents were asked to choose between MRT and e-scooter in each scenario. A questionnaire example is presented in Appendix F.

The stated preference survey was sent to more than 10000 Neuron e-scooter sharing registered users through an online platform from November 26th, 2018 to December 6th, 2018. The users mainly include white-collar workers, students, and tourists in SCA. Finally, 758 complete responses were returned (148 for group 1, 152 for group 2, 142 for group 3, 158 for group 4, and 158 for group 5), with a response rate of about 7.58% and consisting of 5366 answers to all 34 scenarios. The response rate was high compared with normal online survey, because the respondents received coupons as a monetary incentive to participate in the survey. Table 2 illustrates the sociodemographic statistics of all survey respondents and compares it with 2018 Singapore census. The percentages of age below 22 and age above 46 in survey respondents are lower than that in Singapore general population, while the percentage of age 23-45 is higher, indicating that shared e-scooters attract more young and middle-aged adults than other age groups. The male ratio of survey respondents is nearly 75%, which is much higher than 49% in Singapore census, possibly because males are more willing to embrace new technology or more responsive to surveys. The portion of monthly income group below 1500 SGD in respondents is higher than that in general population. This is probably because higher-income people prefer to use other motorized modes more than e-scooters.

Table 2. Sociodemographic statistics of respondents to the stated preference survey

	Stated preference survey respondents		2018 Singapore census
Age			
22 and younger	117	15.44%	24.13%
23-28	200	26.38%	10.59%
29-34	196	25.86%	7.04%
35-45	187	24.67%	15.44%
46-65	57	7.52%	29.77%
Above 65	1	0.13%	13.03%
Gender			
Female	186	24.54%	50.99%
Male	564	74.41%	49.01%
Prefer not to answer	8	1.05%	
Monthly income			
SGD 1500 and below	164	21.64%	16.41%
SGD 1501- SGD 3000	175	23.09%	25.48%
SGD 3001- SGD 5000	123	16.23%	24.70%
SGD 5001- SGD 8000	86	11.34%	16.60%
SGD 8001 and above	105	13.85%	16.81%
Prefer not to answer	105	13.85%	

Source of 2018 Singapore census: the age and gender statistics are from Singapore Department of Statistics; the monthly income statistics are from Singapore Ministry of Manpower, employed residents aged 15 and over by gross monthly income from work.

3.3 Logit models

(1) Multinomial logit model

We first constructed a multinomial logit model as a base model to examine the survey data. Considering the collinearities between MRT travelling time and other MRT variables as well as between e-scooter travelling time and e-scooter fare in design of stated preference survey, we exclude MRT travelling time (T_m) and e-scooter travelling time (T_{es}) from the logit models. We also add a variable of respondents' past e-scooter experience (E_{es}) into the model inputs which is measured by a respondent's total e-scootering time (minute) in the one month before the stated preference survey. We obtained the information of respondents' past e-scooter experience by linking their ID to their trip history.

The e-scooter utility (U_{es}) and MRT utility (U_m) could be written as:

$$U_{es} = \alpha_{es} + \beta_f \cdot F_{es} + \beta_e \cdot E_{es} + \varepsilon_{es} \quad (1)$$

$$U_m = \alpha_m + \beta_f \cdot F_m + \beta_s \cdot S_m + \beta_r \cdot R_m + \beta_w \cdot W_m + \varepsilon_m \quad (2)$$

Where α_{es} and α_m are the alternative specific constants (ASC) of the mode e-scooter and MRT, indicating the preference on that mode. The ASC of mode MRT is normalized to zero. F_{es}, E_{es}, F_m, S_m, R_m, W_m are the variables that determine the utilities and are in alignment with the variable settings in the stated preference survey. β is a series of coefficients to be estimated. ε_{es} and ε_m are the error terms.

The probability of choosing e-scooter (P_{es}) and MRT (P_m) could be written as:

$$P_{es} = \frac{e^{U_{es}}}{e^{U_{es}} + e^{U_m}} \quad (3)$$

$$P_m = 1 - P_{es} \quad (4)$$

(2) Mixed logit model with random parameters

To account for the random tastes among respondents in parameters, we develop a mixed logit model with the integrals of standard logit probabilities over the density of parameters:

$$P_{ni}(\beta) = \int L_{ni}(\beta) f(\beta|\theta) d\beta \tag{5}$$

where P_{ni} is the probability of individual n choosing alternative i, $L_{ni}(\beta)$ is the logit probability evaluated at parameters β:

$$L_{ni}(\beta) = \frac{e^{U_{ni}(\beta)}}{\sum_j^J e^{U_{nj}(\beta)}} \tag{6}$$

and $f(\beta|\theta)$ is the density function of β described by the parameter θ. The distribution of $f(\beta|\theta)$ is usually a normal distribution, a lognormal distribution, or a triangular distribution according to actual conditions. Therefore, the estimation of parameters β becomes the estimation of parameter θ.

(3) Individual-specific error components

Since there are repeated choices of the same individuals in the stated preference survey, we then consider the panel effect of correlation among the responses of the same individuals by including individual-specific error components into mixed logit models. The utility of choosing alternative i for individual n can be defined as:

$$U_{ni} = \alpha_i + \tau_{ni} \cdot Z_n + \beta_{random} \cdot X_i + \rho_{ni} \cdot Z_n + \varepsilon_i \tag{7}$$

where $\rho_{ni} \cdot Z_n$ is the individual-specific error component with ρ_{ni} as a vector of random terms of zero means and Z_n as the observed variables of individual n, and ε_i is the error term with independent and identically distributed extreme value (IID EV). That is, $\rho_{ni} \cdot Z_n + \varepsilon_i$ defines the stochastic portion of utility and can be correlated among the same individuals according to the specification of Z_n. β_{random} are the random parameters and X_i are observed variables related to alternative i. α_i is the ASC of alternative i. We also include $\tau_{ni} \cdot Z_n$ as the individual heterogeneity in ASC depending on the observed variables Z_n of individual n with τ_{ni} as fixed parameters.

(4) Individual heterogeneity around the means of random parameters

To capture additional panel effect of correlation among the responses of same individuals that is not accounted for by error components, we further inject individual heterogeneity into the means of random parameters. We denote that the random parameters β_{random} follow normal distributions and take the form as:

$$\beta_{random} = \mu + \sigma \cdot v \tag{8}$$

where μ are the means and σ are the standard deviations of β_{random}, and v is a standard normal distribution with the mean of 0 and the standard deviation of 1.

To allow for individual heterogeneity around the means of random parameters, we adapt the methods by Greene and Hensher (2006) and Beville and Kerr (2009) and specify μ as:

$$\mu = \beta_0 + \delta \cdot G_n \tag{9}$$

where the means μ are heterogeneous according to the observed variable G_n of individual n, and β_0 and δ are the fixed parameters that capture the mean shift in random parameters.

3.4 E-scooter trip data processing

We acquired 23319 Neuron e-scooter trips containing origins and destinations during one-month period from October 15th, 2018 to November 14th, 2018. These trips both started and ended in SCA. The data had been preprocessed to remove unrealistically short trips of less than 1 minute and long trips of more than 900 minutes. Around 400 e-scooters were in operation. Users were required to park e-scooters at designated parking locations inside the geo-fenced area. Otherwise, users would be penalized with a convenience fee of 5 SGD if not returning e-scooters to the parking locations, or rewarded with an incentive fee of 2 SGD if taking e-scooters that were previously outside parking locations back to the parking locations.

Commuting e-scooter trips during MRT operation hours were selected from the dataset. First, 23319 e-scooter trips were divided into three categories in Table 3, namely 15070 one-way trips of origins and destinations both inside the parking locations (type A), 6839 round trips with overlapped origins and destinations inside the parking locations (type B), and 1410 one-way trips with either origins or destinations or both outside the parking locations (type C). To select the e-scooter trips that were comparable to MRT ones in SCA, we removed the detoured type A trips (indirectness above 5) and type B trips because they were more likely for tourism and sightseeing purposes, and we removed type C trips because they were associated with extra convenience fee or incentive fee that did not match normal cases in our stated preference survey. After that, we obtained 12695 non-detoured type A trips (indirectness below 5) which were more likely for commuting purposes of work-related business and personal errands. We further removed the e-scooter trips off the MRT operation hours (06:38-23:45) and finally filtered out 11640 non-detoured type A trips to represent commuting e-scooter trips during MRT operation hours for addressing RQ2 and RQ3.

Table 3. Descriptive statistics of e-scooter trips

Type of trips		Trip #	Trip %	Trip time (minute)		Trip mileage (km)	
				Mean	Stdev.	Mean	Stdev.
A: One-way trip with OD both inside the parking locations	Non-detoured (Indirectness <= 5)	12695	54.44%	21.48	34.01	2.132	2.033
	Detoured (Indirectness > 5)	2375	10.19%	74.12	79.32	7.753	5.463
B: Round trip with overlapped OD inside the parking locations		6839	29.33%	23.99	49.76	2.203	3.531
C：One-way trip with OD either or both outside the parking locations		1410	6.04%	36.50	45.13	3.955	4.472
Total		23319	100%				

4. Results

4.1 Users' perceptions: stated preference survey to measure mode choices of e-scooters and transit

4.1.1 Logit models

We investigate what variables and how they determine users' mode choices of e-scooter sharing and transit through a series of logit models in Table 4 (RQ1). Model 1 is a base model with the multinomial logit structure. Model 2 is a mixed logit model with random parameters. Model 3 is model 2 plus individual-specific error components. Model 4 is model 3 plus gender heterogeneity around means of random parameters. All models are estimated with maximum likelihood method using R packages. In the mixed logit model 2, model 3, model 4, we use normal distributions for random parameters which perform optimal model fit and generate behaviorally meaningful results.

Looking into the parameter estimates of the multinomial logit model 1, MRT transfer, MRT access-egress walking distance, and fare have significantly negative impacts in determining respondents' mode choices, but the number of MRT stops and respondents' past e-scooter experience are not significant. By fixing the ASC of MRT as zero, the ASC of e-scooters is 0.412, indicating that the respondents in general have a positive preference for e-scooters.

Model 2 accounts for random tastes among respondents by including random parameters into a mixed logit model. The estimates of model 2 produces expected signs. The parameter means are significantly negative for MRT transfer, MRT access-egress walking distance, and fare, but are insignificant for past e-scooter experience and number of MRT stops, which is consistent with the parameter estimates of model 1. The random tastes are confirmed in the significant standard deviation of all parameters except respondents' past e-scooter experience. Model 2 shows additional explanatory power compared to model 1, as the McFadden's pseudo R^2 increases from 0.0813 to 0.2774.

Model 3 extends model 2 by adding individual-specific error components and individual heterogeneity around ASC in e-scooter utilities while fixing those of MRT utilities as zero. E-scooter has a significantly positive ASC by default. Males tend to have a lower e-scooter ASC, but are more heterogeneous in e-scooter preference than non-males. The age groups 23-34 have the lowest e-scooter ASC, and the age group below 22 are most heterogeneous in e-scooter preference. As for the income groups, the higher the income level, the lower the increase in e-scooter ASC, however, the income group 5000-8000 SGD has the most heterogeneous preference for e-scooters. The likelihood ratio-test statistic from model 2 to model 3 is 1036 ($p<0.001$), showing a better model fit for model 3 when including error components and heterogeneity around e-scooter ASC.

Model 4 further injects gender heterogeneity into the means of random parameters. The random parameters of MRT transfer, MRT access-egress walking distance, and fare have significantly negative means by default, which is aligned with model 2 and model 3. Being a male mitigates the average intensity of how MRT transfer and fare affect utilities. When including heterogeneity around the means of random parameters, model 4 shows better measure of goodness-of-fit compared with model 3, as the likelihood ratio-test statistic is 22 ($p<0.001$).

Overall, these findings demonstrate that fare, MRT transfer, and MRT access-egress walking distance have significantly negative impacts on mode utilities with random tastes among respondents. Male, young and high-income groups are more heterogeneous in e-scooter preferences. Also, gender would affect the way of how fare and transit transfer determine the mode choices.

Table 4. Results of logit model 1-4

Attributes	*Alternatives*	Model 1	Model 2 Mean	Model 2 Stdev.	Model 3 Mean	Model 3 Stdev.	Model 4 Mean	Model 4 Stdev.
E-scooter ASC	E-scooter	0.412*	0.476*		1.738*		0.157	
Random parameter								
Past e-scooter experience	E-scooter	-0.000249	0.00056	0.00216	-0.00202*	0.00813*	-0.00158	0.01745*
MRT stop	MRT	0.0445	0.0479	0.2644*	-0.0330	0.7794*	0.0052	0.3568*
MRT transfer	MRT	-0.498*	-1.198*	1.442*	-1.815*	2.389*	-1.146*	2.247*
MRT walking	MRT	-1.228*	-2.201*	1.291*	-3.386*	0.129	-2.873*	0.912*
Fare	E-scooter & MRT	-0.521*	-0.991*	0.813*	-1.655*	1.305*	-1.127*	1.062*
Error components								
Male	E-scooter					2.995*		3.272*
Age ≤22	E-scooter					4.652*		3.455*
Age 23-28	E-scooter					1.635*		0.248
Age 29-34	E-scooter					0.586		0.398
Age 35-45	E-scooter					0.533		0.689
Income ≤1500	E-scooter					15.210*		11.815*
Income 1501-3000	E-scooter					8.043*		8.406*
Income 3001-5000	E-scooter					7.279*		12.239*
Income 5001-8000	E-scooter					21.738*		12.151*
Income > 8000	E-scooter					7.054*		7.049*
Heterogeneity around E-scooter ASC								
Male	E-scooter				-0.663*		0.952	
Age ≤22	E-scooter				-0.175		-0.377	
Age 23-28	E-scooter				-1.354*		-0.386	
Age 29-34	E-scooter				-1.749*		-0.577	
Age 35-45	E-scooter				-1.180*		0.041	
Income ≤1500	E-scooter				3.666*		2.986*	
Income 1501-3000	E-scooter				2.079*		0.693*	
Income 3001-5000	E-scooter				1.493*		1.988*	
Income 5001-8000	E-scooter				2.229*		1.970*	
Income > 8000	E-scooter				0.445		0.022	
Heterogeneity around means of random parameters								
Male * MRT transfer	MRT						0.870*	
Male * MRT walking	MRT						0.369	
Male * Fare	E-scooter & MRT						0.752*	
Summary of statistics								
McFadden's pseudo R^2		0.0813	0.2774		0.4245		0.4275	
Log-Likelihood		-3237	-2546		-2028		-2017	
Number of observations		5366	5366		5366		5366	

Note: * $p<0.05$. The gender, age, and income variables (i.e. Male, Age ≤22, Age 23-28, Age 29-34, Age 35-45, Income ≤1500, Income 1501-3000, Income 3001-5000, Income 5001-8000, Income > 8000) are dummy variables. To avoid collinearity, we exclude females and a small proportion of unknown genders from gender variables, exclude age>45 from age variables, and exclude the unknown income from income variables.

4.1.2 E-scooters mode share by replacing transit trips

We further investigate how many short-distance transit trips are perceived to be possibly replaced by e-scooters (RQ2). We use the trip data introduced in section 3.4 as a proxy of short-distance travel demand and split them into groups on different levels of transit inconvenience. We do a comparison of MRT and e-scooter performances and calculate the e-scooter mode share in each group.

We set different levels of transit inconvenience in Eq (10) and table 5:

$$M_i = \{m \in M \mid I_m > d \,\&\, R_m \geq t \,\&\, W_m \geq w\} \tag{10}$$

where *M* is a collection of all origin-destination (OD) pairs; M_i is a subset at certain level of transit inconvenience, *m* is one OD pair; *d, t, w* are pre-determined thresholds of MRT network indirectness (I_m), MRT transfer (R_m), and MRT access-egress walking distance (W_m). The thresholds of five transit inconvenience levels M_{i1}, M_{i2}, M_{i3}, M_{i4}, M_{i5} are defined in table 5. M'_i is the complement set of M_i and by nature has lower inconvenience than M_i.

Table 5. Thresholds of five transit inconvenience levels

Inconvenience level	Threshold of I_m	Threshold of R_m	Threshold of W_m
M_{i1}	$I_m > 2.276$	$R_m \geq 1$	$W_m \geq 0.6\ km$
M_{i2}	$I_m > d$	$R_m \geq 1$	$W_m \geq 0.6\ km$
M_{i3}	$I_m > d$	$R_m \geq 1$	$W_m \geq 1.2\ km$
M_{i4}	$I_m > d$	$R_m \geq 2$	$W_m \geq 0.6\ km$
M_{i5}	$I_m > d$	$R_m \geq 2$	$W_m \geq 1.2\ km$

The travel demand is firstly categorized into the transit inconvenience level M_{i1} ($I_m > 2.276$, $R_m \geq 1$, and $W_m \geq 0.6\ km$) and its complement set M'_{i1}. We select 2.276 as a threshold of I_m, because it is the average MRT indirectness of observed trips. Fig. 3 presents hourly trip numbers under M_{i1} and M'_{i1}. M_{i1} account for 18.48% short-distance trips which have higher than 2.276 MRT indirectness, at least 1 transfer, and longer than 0.6 km walking distance. Although the trip numbers in M_{i1} and M'_{i1} fluctuate across the day with peaks at 18:00, their percentages remain relatively constant. Fig. 4 shows the spatial distribution of the monthly trip numbers for M_{i1} and M'_{i1} aggregated at origins. Trips with transit inconvenience M_{i1} appear more in SCA core than the periphery, while M'_{i1} are the opposite.

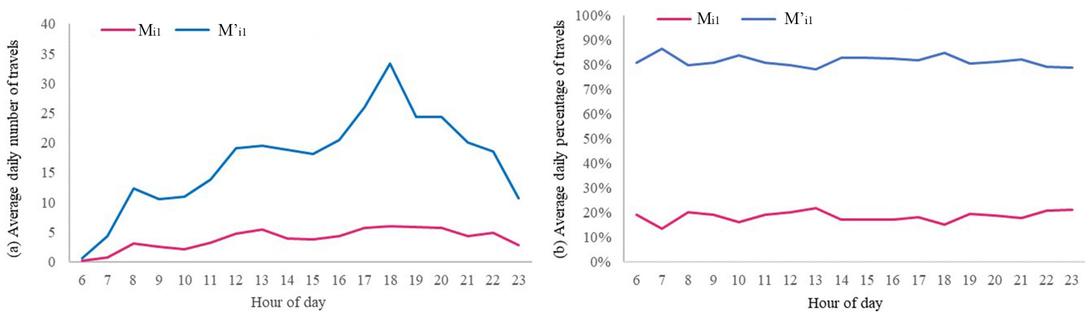

Fig. 3. Hourly number (left) and percentage of trips (right) on MRT inconvenience level M_{i1} and M'_{i1}

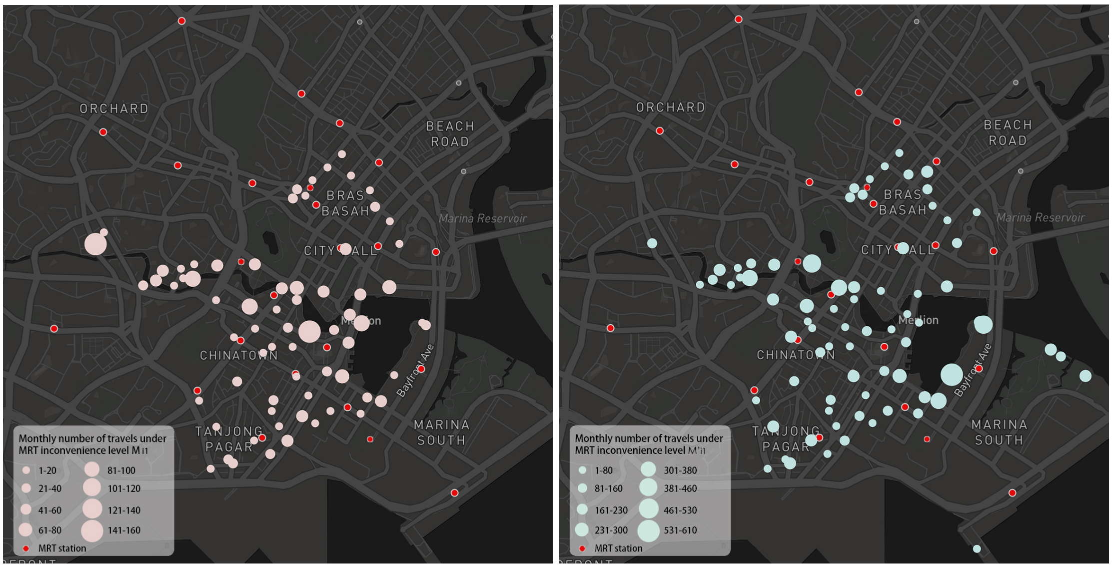

Fig. 4. Monthly number of trips on MRT inconvenience level M_{i1} (left) and M'_{i1} (right) aggregated at origins (starting e-scooter parking locations)

We then do a comparison of e-scooters and MRT performances when serving 18.48% trips under transit inconvenience level M_{i1} and 81.52% under M'_{i1}. The results are shown in Table 6 and Appendix G. Overall, e-scooters are found to generate less average time, mileage, and e-scooter indirectness (e-scooter mileage over the shortest street network distance) for M_{i1} than M'_{i1}. We compute e-scooter mode shares for the two travel demand groups M_{i1} and M'_{i1} using the coefficients derived from the base model 1 in Table 4. The average e-scooter probability is 77.4% for M_{i1} and 57.6% for M'_{i1}. This contrast demonstrates that the less convenient the MRT trips, the more MRT trips would be replaced by e-scooter sharing.

Table 6. Comparisons between MRT and e-scooter performances for M_{i1} and M'_{i1}

		Trips of M_{i1}	Trips of M'_{i1}
E-scooter	Average e-scooter indirectness	1.609	1.664
	Average e-scooter time	18.188 min	21.726 min
	Average e-scooter mileage	1.837 km	2.161 km
MRT	Average MRT indirectness	4.255	1.828
	Average access-egress walking distance	1.131 km	0.880 km
	Percentage of 0 transfer	0.000%	70.102%
	Percentage of 1 transfer	47.420%	21.383%
	Percentage of 2 transfers	49.512%	7.472%%
	Percentage of 3 transfers	3.068%	1.043%%
Average ratio of e-scooter mileage to MRT mileage		0.461	1.132

We further test the sensitivity of e-scooter mode share to transit inconvenience levels by varying the thresholds in M_{i2}, M_{i3}, M_{i4}, M_{i5} in Table 5. We change I_m's threshold d from 1.314 (average value in HITS data) to 10. The results presented in Fig.5 show that 1) the average e-scooter mode share for M_{i2}, M_{i3}, M_{i4}, M_{i5} is always higher than that for their complement set M'_{i2}, M'_{i3}, M'_{i4}, M'_{i5}, where the former is always above 72.2% and the latter remains stable around 60%; 2) under the same MRT transfer and MRT access-egress walking distance threshold, the higher the MRT network indirectness's threshold *d*, the larger the e-scooter probability; 3) the sensitivity to the thresholds of MRT transfer and MRT access-egress walking distance present a similar trend. This sensitivity test corroborates our previous finding in that, although there is no universal benchmark of transit inconvenience, e-scooters would replace more MRT trips whichever have higher inconvenience levels of indirectness, transfer, and walking.

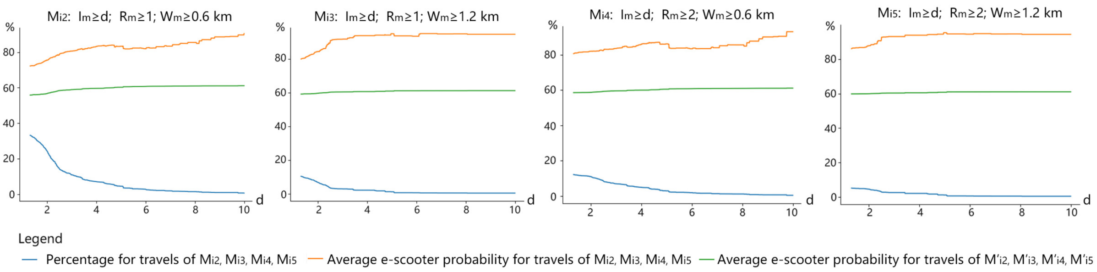

Fig. 5. Sensitivity of e-scooter mode share to MRT inconvenience levels

4.2 Operational trade-offs between e-scooter mode share maximization and revenue maximization

The objectives of serving more e-scooters trips (mode share maximization) and seeking more revenue (revenue maximization) are not always aligned. The previous sections ascertain the fact that people tend to use e-scooters more when the short-distance transit trips have higher inconvenience level of indirectness, transfer, and walking. This implies an induced need for short-distance travel options and a potential market for e-scooter sharing. Serving more trips or attracting more users might be the central concern when an e-scooter company is initially launched. However, the private company will inevitably seek higher revenue in the long run. As outlined in RQ3, understanding the trade-offs between mode share maximization and revenue maximization becomes important to inform public policy making. In this section, using the observed trip data as a proxy of short-distance travel demand, we investigate the alignment and discrepancy between the goals of gaining e-scooter mode share and revenue, compare the conflicts between the mode share maximization and revenue maximization under a dynamic pricing, and discuss possible trade-off strategies between two objectives.

We start to understand the relationship between mode share maximization and revenue maximization in two hypothetical cases, as shown in Fig. 6. First, for each e-scooter OD pair, we compute e-scooter mode share and revenue with varying e-scooter fare (F_{es}). E-scooter mode share is approximated by e-scooter probability (P_{es}), computed using F_{es} in Eq (1), (2), (3). The coefficients are derived from base model 1 in Table 4. E-scooter revenue is then measured as $V_{es} = P_{es} * F_{es}$. The difference between case 1 and 2 in Fig 6 is whether the probability of choosing e-scooter is higher than transit when the revenue reaches its maximum. In Fig. 6, three critical points are identified. Q is when the probability of choosing e-scooter (P_{es}) is the same as choosing MRT (P_m), which is also the point when probability shows the most decreasing rate (the first derivative is lowest). N is the e-scooter revenue (V_{es}) tipping point where it reaches the maximum. L is the point where e-scooter revenue (V_{es}) has the most decreasing rate. Using these critical points, five stages of e-scooter services A1-A5 can then be classified as shown in Fig 6. There are two sequences of point Q, N, L: either Q is between N and L (case 1), or N is between Q and L (case 2).

A1-A5 show different stages in any of which e-scooter probability and revenue increase or decrease monotonically, as summarized in Table 7. The goal of mode-share-seeking is aligned with revenue-seeking in A1, A2 and A3 stages, because e-scooter probability and revenue curves have the same monotonicity. On the contrary, there is discrepancy between two goals in A4 and A5 stages due to their opposite monotonicity. Notably, A5 has much sharper discrepancy than A4, because a decreasing rate of revenue growth coincides with an increasing rate of probability decline in A5 but a decreasing rate of probability decline in A4.

We divide the travel demand into trips under A1-A5 e-scooter services by which stage its e-scooter fare falls in. Fig. 7 reports the numbers of travel demand under A1-A5 e-scooter services in hours of day and aggregated at origins. A1-A4 have only small trip volumes of mild hourly fluctuations, with hot spots along the Singapore river. But A5 shows a much larger trip volume, with the temporal peak hours in 8:00, 13:00, 18:00 and an evenly spatial distribution in SCA. The large volume of A5 indicates that the majority of e-scooter services has intensive conflicts between its mode share increase and revenue increase.

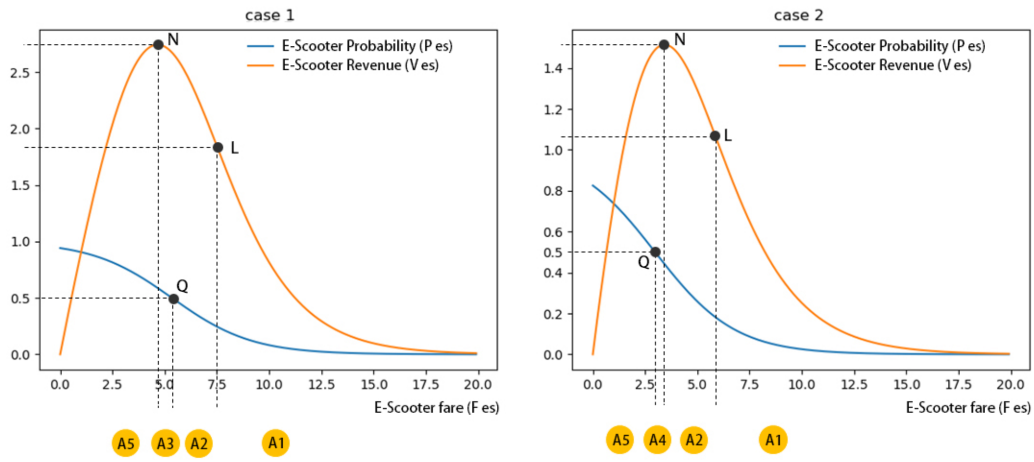

Fig. 6. E-scooter mode share (probability) and e-scooter revenue in relationship to e-scooter fare

Case 1: Q is between N and L, using ($F_m = 0.77,\ R_m = 1,\ W_m = 1.2\ km$) as an example

Case 2: N is between Q and L, using ($F_m = 0.77,\ R_m = 0,\ W_m = 0.6\ km$) as an example

Table 7. Impact of reducing e-scooter fare on e-scooter probability and revenue for A1-A5 stages

E-scooter stages	When reducing e-scooter fare (F_{es})	
	E-scooter probability (P_{es})	E-scooter revenue (V_{es})
A1	Increases at an increasing rate	Increases at an increasing rate
A2	Increases at an increasing rate	Increases at a decreasing rate
A3	Increases at a decreasing rate	Increases at a decreasing rate
A4	Increases at an increasing rate	Decreases at an increasing rate
A5	Increases at a decreasing rate	Decreases at a decreasing rate

Fig. 7. Numbers of travel demand under A1-A5 e-scooter services: average daily number in hours of the day and monthly number aggregated at origins (e-scooter starting parking locations)

When the e-scooter company adjusts the fare to increase e-scooter mode share in each OD segment, what could be the impact on e-scooter revenue and vice versa? To maximize the revenue, the fare needs to be adjusted to the point N in Fig. 6; and to maximize mode share (probability), the fare needs to be adjusted to a lower fare in which the service can still be sustained economically. In this work, the fare lower bound is set to be the minimum cost calculated on the current fare structure (1 SGD to start and 0.12 SGD per other minute) by assuming that users spend the shortest time and follow the shortest road path at the allowable maximum speed of non-motorized vehicle in Singapore (15 km/h). The e-scooter fare lower bound is smaller than the fare at revenue maximum point N for all A1-A5 services. Only for a few 5.24% A5 services, the fare is already lower than the fare lower bound, and thus will not be adjusted in probability maximization. We compute individual trip's e-scooter probability change and revenue change under either probability maximization or revenue maximization, and show two changes in a bi-dimensional histogram in Fig. 8. Table 8 show change in average e-scooter probability and revenue totals for all trips under two maximizations. This comparison ascertains that the loss of revenue and e-scooter mode share can reach as high as 26.02% and 16.64% if blindly maximizing the other one. With respect to the percentage change, revenue maximization brings more gains with less loss than mode share maximization.

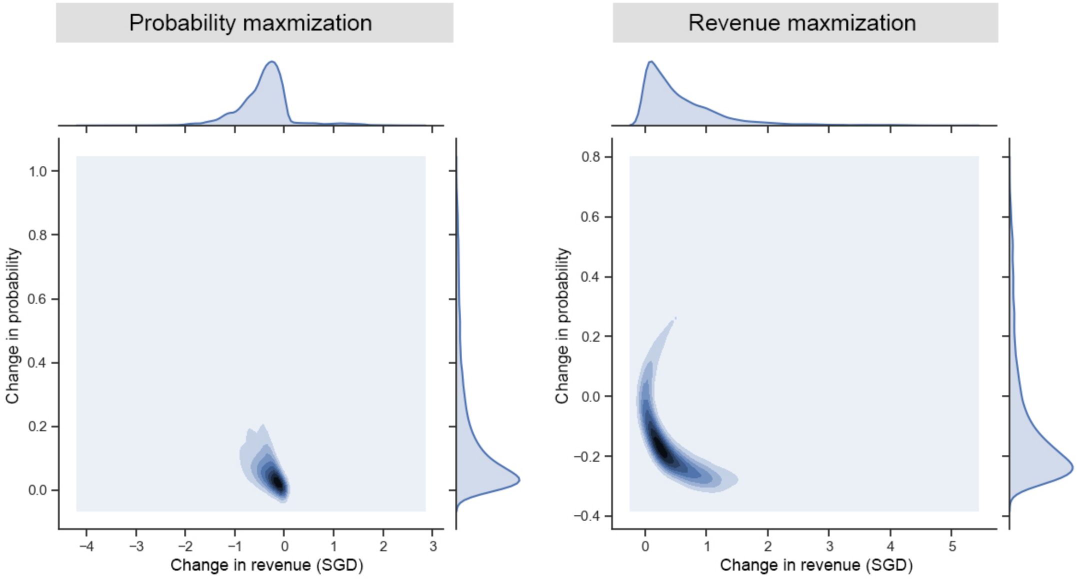

Fig. 8. Change in e-scooter probability (x-axis) and revenue (y-axis) for individual trips: e-scooter probability maximization (left) and revenue maximization (right)

Table 8. Change in average e-scooter probability and total revenue for all trips

	Average e-scooter probability	Total e-scooter revenue (SGD)
Original value	0.613	18409.108
Change after e-scooter probability maximization	+0.165 (Increase by 26.92%)	-4789.952 (Decrease by 26.02%)
Change after e-scooter revenue maximization	-0.102 (Decrease by 16.64%)	+6914.401 (Increase by 37.56%)

Given that maximization of one objective would result in loss of the other, a win-loss situation, how do we balance two maximizations so to serve more trips without much sacrifice in revenue, and vice versa? We answer this question by exploring the solutions that could reduce two goals' discrepancy. The trade-off solutions for A1-A5 services are summarized in Table 9. Under e-scooter probability maximization, a possible trade-off solution for A1, A2, A3 is to stop reducing fare at the revenue maximum point N, or to a lower fare of higher probability but the same revenue. A trade-off solution for A4 services is to stop reducing fare at point Q where probability increases the fastest. A trade-off solution for A5 services could be adjusting the fare to the middle point between current fare and the fare lower bound. Similarly, under e-scooter revenue maximization, a possible trade-off solution for A5 services in case 2 of Fig.6 is to adjust the fare to point Q. The results of these trade-off solutions are compared and shown in the last two columns of Table 9, which reports a pronounced save of the decrease in one end, while still maintaining a significant increase in the other. Taking the large volume of A5 e-scooter services as an example, maximizing the probability for A5 services whose fare lower bound is smaller than current fare would increase their average probability by 10.83% and decrease the total revenue by 30.65%. But the trade-off solution to the middle point could save the total revenue decrease to 13.12% and still maintain 5.92% increase in the average probability. Likewise, maximizing the revenue for A5 services in case 2 increases their total revenue by 28.37% and decreases the average probability by

30.76%. But the trade-off solution could save the average probability decrease to 19.34% and still generate 23.76% increase in the total revenue. In sum, these trade-off strategies provide a useful tool for e-scooter company and public authority to consider a balance between the two different goals of mode share and revenue.

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Table 9-1. Trade-offs for e-scooter probability maximization

E-scooter service		Average probability_ original value	Overall revenue (SGD)_original value	Fare adjustment strategies (* indicates the trade-off solutions)	Average probability _change	Total revenue (SGD)_change
A1, A2, A3	Revenue at fare lower bound >= current revenue	0.076	480.302	To the fare lower bound	+0.678 (+894.61%)	+661.280 (+137.68%)
				To the fare at point N*	+0.440 (+580.77%)	+1278.445 (+266.18%)
	Revenue at fare lower bound < current revenue	0.381	2422.930	To the fare lower bound	+0.388 (+101.84%)	-1081.443 (-44.63%)
				To a lower e-scooter fare of the same revenue but higher probability*	+0.249 (+65.42%)	0.000 (0.00%)
				To the fare at point N*	+0.131 (+34.39%)	+347.072 (+14.32%)
A4		0.451	844.021	To the fare lower bound	+0.137 (+30.38%)	-267.191 (-31.66%)
				To the fare at point Q*[6]	+0.049 (+10.76%)	-62.700 (-7.43%)
A5	Current fare <= fare lower bound	0.828	505.175	No fare adjustment	0.000 (0.00%)	0.000 (0.00%)
	Current fare > fare lower bound	0.721	13386.276	To the fare lower bound	+0.078 (+10.83%)	-4102.597 (-30.65%)
				To the middle point of fare lower bound and current fare*	+0.043 (+5.92%)	-1756.880 (-13.12%)

[6] For 0.24% of A4 whose fare lower bound is larger than that at point Q, the services' fare is adjusted to the fare lower bound.

Table 9-2. Trade-offs for e-scooter revenue maximization

E-scooter service		Average probability_ original value	Overall revenue (SGD)_original value	Fare adjustment strategies (* indicates the trade-off solutions)	Average probability _change	Total revenue (SGD)_change
A1, A2, A3		0.281	3673.636	To the fare at point N	+0.233 (+82.92%)	+1625.517 (+44.25%)
A4		0.451	844.021	To the fare at point N	-0.096 (-21.30%)	+68.372 (+8.10%)
A5	Case 1: fare at point N<fare at point Q< fare at point L	0.786	10504.988	To the fare at point N	-0.207 (-26.28%)	+4259.767 (+40.55%)
	Case 2: fare at point Q<fare at point N< fare at point L	0.620	3386.463	To the fare at point N	-0.191 (-30.76%)	+960.746 (+28.37%)
				To the fare at point Q*	-0.120 (-19.34%)	+804.648 (+23.76%)

5. Discussions

E-scooter sharing is an emerging mobility service. This work pioneers the study of using e-scooters to replace short-distance transit trips of excessive indirectness, multiple transfers, and long access-egress walking. We focus on two facets, namely (1) the perceptional acceptance of using e-scooters based on a stated preference survey, and (2) the operational trade-off between e-scooter mode share and revenue. The findings offer insights into how these services could be utilized and regulated to e-scooter operators, transportation planners, and policy makers.

On the first facet, analyses show that transit transfer and access-egress walking distance significantly reduce transit mode share, and e-scooters are perceived to have higher potentials of replacing short-distance transit trips of greater indirectness, transfer, and walking. This deepens our understanding about where and how to deploy e-scooters to effectively satisfy the demand unmet by transit. The appropriate locations to supply e-scooters are either the point far from any transit stations or around transit stations that have a high possibility of transfers to other stations in SCA (e.g. Bencoolen station, Raffles Place station, City Hall station, etc.). Also, the analyses reveal that sociodemographic features would affect the way of how fare and transit transfer influence mode choices. This provides references for precise e-scooter supply strategies. For example, in the blocks where people are more sensitive to transit transfer, more resources of e-scooters can be provided.

Using e-scooter sharing to replace short-distance MRT trips in SCA can ease MRT congestion during peak hours. For the purpose of reducing MRT crowding, Singapore Land Transport Authority launched the program of Travel Smart Journeys in 2019. It includes incentivizing the public to reconsider other green modes during peak hours, such as personal mobility devices. Shared e-scooters provide an alternative transport option to alleviate MRT crowding in SCA as our analyses show that e-scooters are competitive to serve MRT trips with higher than 2.276 network indirectness, at least 1 transfer, and longer than 0.6 km walking distance. Considering the limited urban space for e-scooter supply, it is worth further investigations in how to smartly allocate e-scooters spatially and manage supply during hours of day for satisfying short-distance travel demand.

On the second facet, trade-off solutions are compared to leverage on the objectives of e-scooter mode share and revenue. The principle of our suggestions is to increase mode share without much sacrificing in revenue. What a specific trade-off strategy to select should be based on the value judgement of loss. For probability maximization in A1, A2, A3 services, if the revenue loss is compared to the initial revenue before adjustment, a proper trade-off solution is to stop reducing fare where the revenue is as same as before. However, if the revenue loss is compared to the maximum revenue, an ideal trade-off strategy is to stop reducing fare at revenue maximum point. Also, the objectives of the private e-scooter company and urban transport authorities are not always aligned. This could happen when the private company seeks for higher revenue and mitigate e-scooter supply where affordable and convenient connections are needed but not profitable. As Singapore Land Transport Master Plan 2040 highlights the importance of harnessing the strength of new mobility services to provide more point-to-point transport options, the behavior of private e-scooter operators should be regulated to reach a proper balance between e-scooter mode share and revenue and between private operators and public transport authorities.

Moreover, e-scooters involves safety and nuisance concerns that are revealed as a barrier to people's decision making in shifting to micro-mobility. This has aroused wide attentions. In e-scooter pilot programs of US cities, road safety is a prior consideration in operators' permit application, including helmet requirement, headlamp and rear reflector installation, device and battery safety test, education on users to obey traffic rules, congestion pricing to reduce injuries, etc. (Wood et al., 2019; Riggs and Kawashima, 2020). More than relying on private companies to implement safety rules, Singapore Land Transport Authority is planning for more cycling path in the near future to accommodate electronic micro mobilities, in order to reduce conflicts in right of way and enhance road safety. It has triggered dialogues among operators, users, and legislators about urban design and planning for a safer street infrastructure. As for e-scooter nuisance, parking chaos has become a major problem in many cities (James, 2019). For example, the random e-scooter parking might block the walkways and car parking space, become an easy target for public space vandalism, and cause disturbance to road traffic. To keep street neat and free of obstructions, shared e-scooters are required to park at the street furniture zones in Washington D.C. (District Department of Transportation, 2020), and at the designated parking zones with markers or racks in Singapore (Land Transport Authority, 2020). Another concern is uncontrolled expansion of e-scooter fleet size (Hall et al., 2019). Operator fleet caps are also adopted in Singapore to limit the quota of each operator and regulate their supply deployment. All of these indicate that proper regulations on e-scooters are necessary and are the prerequisite for smart use of this new mobility.

Some limitations remain in this study. First, the stated preference survey was conducted to only e-scooter users through collaborations with Neuron. This guaranteed that all respondents were familiar with e-scooter concept, but it would inevitably result in a selection bias. As all the respondents are already e-scooter users, the potential of e-scooter usage for short transit trips could be overestimated. The future research shall seek to recruit more non-users, which can reduce the bias and allow for a random control trial. The stated preference survey was conducted from November 26th, 2018 to December 6th, 2018, which had more rainfalls and lower mean daily temperature than other seasons and might lead to the lower likelihood of using shared e-scooters. More supplementary survey during other seasons can be added in further studies. Second, due to the limited access to the full travel demand data, we used the observed e-scooter trips as a proxy of short-distance travel demand. This reflects the real e-scooter fare and time than a hypothetical case, but is subject to the data bias toward the use of e-scooters. In further studies, other sources of trips would be helpful to serve as a supplement, such as transit trips. Also, as the e-scooter trips were obtained one month before the stated preference survey, the changes in weather might have an impact on the travel behavior. The survey time overlapped with the monsoon seasons in Singapore and therefore had more rainfalls than the one month before the survey. As a consequence, respondents might be more inclined to shared e-scooters in the one month before the survey. Additionally, given that e-scooter trips only have the information of origins and destinations inside parking locations, we did not include the walking distance accessing and egressing the e-scooter parking locations. In SCA, users walk for 0.2 km on average to reach e-scooter parking locations. More precise travel demand data would allow for a better depiction of real situations. Third, in designing the stated preference survey, the average MRT travelling time was estimated using other MRT variables, and e-scooter travelling fare was computed using e-scooter travelling time based on Neuron's real pricing structure. Therefore, MRT and e-scooter travelling time were excluded from the logit model inputs. Their effects have been accounted through including these other variables. However, in other studies, to understand the effect of travelling time on utilities independently, we would need the traveling time to be not associated with other variables, and this needs further inspections. Future work shall expand the survey respondents and vary the survey timing, test the survey results on multiple-sourced and more precise travel demand data, and account for situations where travelling time can have an independent impact on mode choices.

Future research may consider to explore the potential of e-scooter sharing in the following aspects. 1) Built environment can influence individual transit modal shift to shared micro mobilities (Martin and Shaheen, 2014). How the factors, like urban density, land use diversity, street design, and sociodemographic features, impact on e-scooter sharing needs further examination. Comparative studies across multiple cities are demanded to gain general insights into promoting e-scooter sharing. 2) In addition to transit network indirectness, transfer, and access-egress walking distance, other factors of transit services can also affect transit experience, therefore influencing transit modal shift. For example, the effects of transit punctuality, reliability, environment inside carriages and congestion level during peak hours need further investigation. 3) There are other factors besides revenue for an e-scooter operator to consider, such as viscosity of users and advertisement effectiveness. Comprehensive discussions of those trade-offs can be conducted. 4) As shared e-scooters have potentials to serve short-distance transit trips, future research on fleet size management and rebalancing shall be considered. How to find optimal e-scooter distributions spatially and temporarily according to the varying travel demand unsatisfied by transit is worth investigations. 5) Safety, nuisance, and lack of bike lanes have become major barriers for shared e-scooters (Shaheen and Cohen, 2019). It is worth more explorations in planning and policy toolkits about regulating e-scooters, such as curb space management, parking guidelines, safety rules, fleet caps, and design of dedicated paths.

6. Conclusions

The emergence of e-scooter sharing as a new micro mobility service provides an attractive option for short-distance travelers. Surprisingly less was known about its effectiveness in serving short-distance transit trips. In this work, we investigate the potential of using e-scooter sharing to replace short-distance transit trips in Singapore Central Area on two levels, namely users' perceptional level and e-scooter companies' operational level. Through a stated preference survey and mixed logit models, we find that fare, MRT transfer, and MRT access-egress walking distance have significantly negative impacts on mode utilities with random tastes among respondents. Male, young and high-income groups are more heterogeneous in e-scooter preferences. In analyzing the travel demands under different levels of transit inconvenience, we discover that higher level of transit indirectness, more transfers, and longer access-egress walking result in a higher probability of using e-scooters. Through analyzing the decision of e-scooter companies in terms of the trade-offs between serving more e-scooter trips and making more revenue under varying fares, we find that the revenue loss can be significant if to blindly maximize e-scooter's mode share, and vice versa. To achieve a better balance between two goals, we figure out the trade-off places in-between two maximization extremes that could save much loss in one by only a small decrease in the maximized amount of the other, through keeping two goals' alignment and reducing their discrepancy. This study would inform operators, planners and policy-makers on how to harness and regulate this new mobility service. It provides suggestions on deploying shared e-scooters to satisfy the demand unmet by transit, especially where transit travels have greater indirectness, transfer, and access-egress walking distance. E-scooter supply strategies at different locations can be varied according to the sociodemographic features which influence e-scooter preference and mode choices. When public authorities and private operators have conflicts in serving more individual trips and seeking more revenue, the trade-off can be gauged to achieve a proper balance. The possible means include administrative regulations (i.e. issue the operator permit which requires operators to serve inconvenient short transit trips at some designated locations) or economic interventions (i.e. subsidies to operators provided by public authorities).

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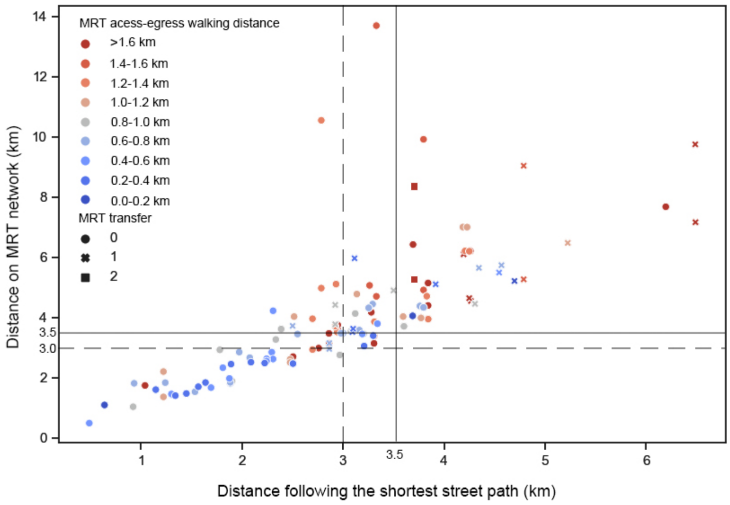
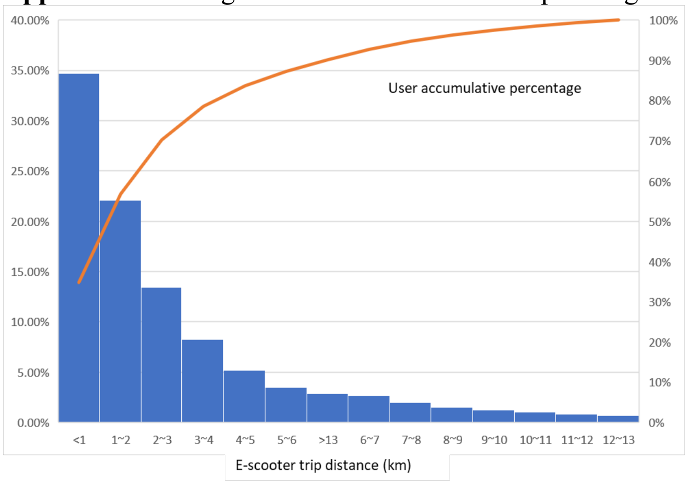
Appendix A. Typical scenarios that shared e-scooters are competitive to MRT in SCA

Origin MRT station	Destination MRT station	MRT traveling time (Min)	MRT transfers	MRT fare (SGD)	E-scooter travelling time (Min)	E-scooter fare (SGD)
Tanjong Pagar	Telok Ayer	26	2	0.77	6	1.60
Tanjong Pagar	Downtown	30	2	0.77	6	1.60
Tanjong Pagar	Marina Bay	15	1	0.77	10	2.08
Downtown	Raffles Place	26	2	0.77	8	1.84
Fort Canning	Clark Quay	15	1	0.77	8	1.84
Fort Canning	Dhoby Ghaut	20	1	0.77	10	2.08
City Hall	Esplanade	20	1	0.77	5	1.48
Rochor	Bencoolen	30	2	1.07	6	1.60
Bugis	Bencoolen	30	0	1.07	8	1.84
Bras Basch	Bugis	20	1	0.77	8	1.84
Esplanade	Bugis	15	1	0.77	6	1.60
Dhoby Ghaut	Bencoolen	25	1	0.87	6	1.60
Raffles Place	Clark Quay	17	1	0.87	10	2.08
Downtown	Marina Bay	15	1	0.77	4	1.36
Raffles Place	Telok Ayer	22	2	0.87	4	1.36

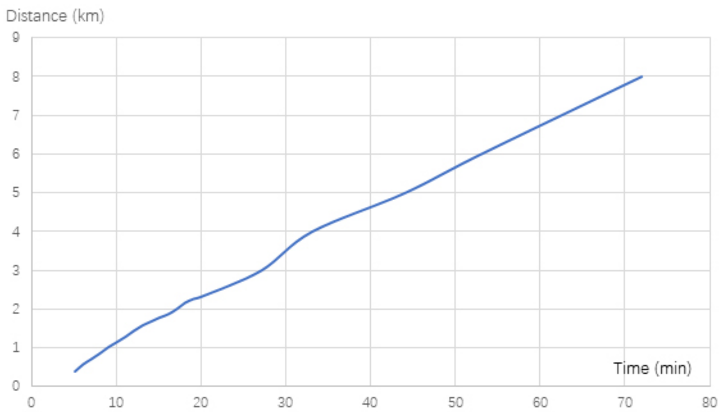
Appendix B. Statistics of MRT trips that started and ended in SCA. Data is from 2012 Singapore Household Interview Travel Survey.



Appendix C. Histogram of Neuron e-scooter trip mileage in SCA



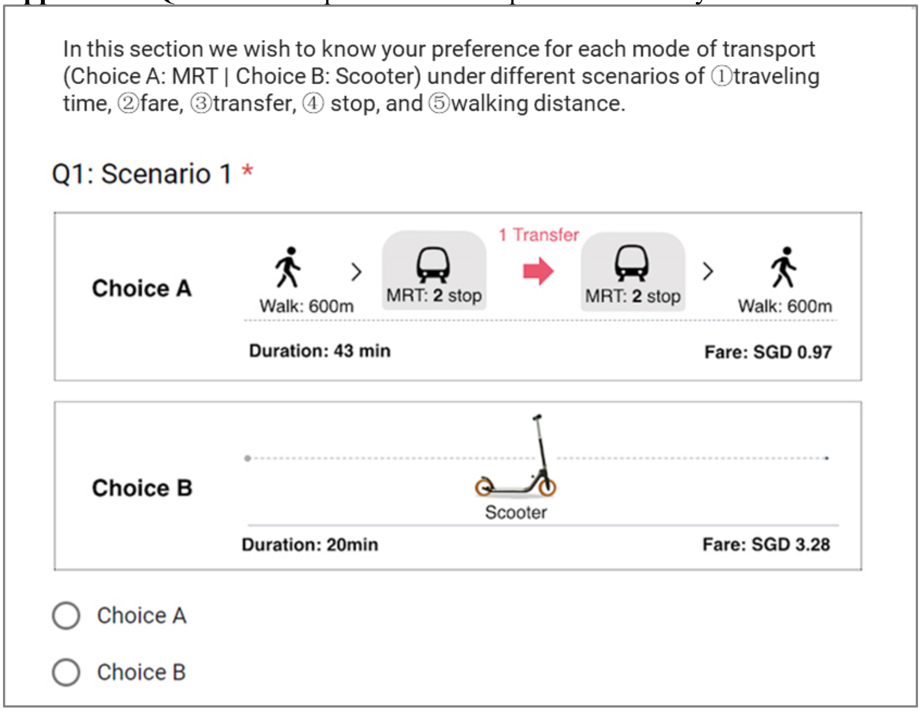
Appendix D. Time-distance relation of Neuron e-scooter trips in SCA



Appendix E. Experimental design of the stated preference survey. 34 scenarios were divided into 5 questionnaire groups, following the principals that: (1) each group contained 6-7 scenarios where the scenarios in favor of either MRT or e-scooter were evenly and proportionally distributed to avoid self-enhancement; (2) the 6-7 scenarios in each group covered all levels of each variable.

Scenario	S_m Number of MRT stop	R_m MRT transfer	W_m MRT access-egress walking distance (km)	T_{es} E-scooter travelling time (minute)	T_m MRT travelling time (minute)	F_m MRT fare (SGD)	F_{es} E-scooter fare (SGD)	Questionnaire Group
1	2	0	0.6	10	23	0.77	2.08	1
2	2	0	0.6	20	23	0.77	3.28	2
3	2	0	1.2	10	35	0.77	2.08	1
4	2	0	1.2	20	35	0.77	3.28	2
5	2	0	1.2	30	35	0.77	4.48	3
6	2	1	0.6	10	26	0.77	2.08	1
7	2	1	0.6	20	26	0.77	3.28	2
8	2	1	1.2	10	38	0.77	2.08	5
9	2	1	1.2	20	38	0.77	3.28	2
10	4	0	0.6	20	28	0.97	3.28	4
11	4	0	1.2	20	40	0.97	3.28	1
12	4	0	1.2	30	40	0.97	4.48	1
13	4	1	0.6	10	31	0.97	2.08	4
14	4	1	0.6	20	31	0.97	3.28	4
15	4	1	0.6	30	31	0.97	4.48	3
16	4	1	1.2	10	43	0.97	2.08	2
17	4	1	1.2	20	43	0.97	3.28	2
18	4	1	1.2	30	43	0.97	4.48	3
19	4	2	0.6	10	34	0.97	2.08	4
20	4	2	0.6	20	34	0.97	3.28	5
21	4	2	0.6	30	34	0.97	4.48	5
22	4	2	1.2	10	46	0.97	2.08	4
23	4	2	1.2	20	46	0.97	3.28	1
24	4	2	1.2	30	46	0.97	4.48	3
25	6	0	0.6	30	33	1.07	4.48	4
26	6	0	1.2	30	45	1.07	4.48	5
27	6	1	0.6	30	36	1.07	4.48	4
28	6	1	1.2	30	48	1.07	4.48	5
29	6	2	0.6	10	39	1.07	2.08	5
30	6	2	0.6	20	39	1.07	3.28	3
31	6	2	0.6	30	39	1.07	4.48	5
32	6	2	1.2	10	51	1.07	2.08	3
33	6	2	1.2	20	51	1.07	3.28	3
34	6	2	1.2	30	51	1.07	4.48	2

Appendix F. Question example of the stated preference survey



Appendix G. Bi-directional histogram of travel demands under transit inconvenience level M_{i1} (left) and M'_{i1} (right)