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Modelling the complementarity and flexibility between different shared modes available in smart electric mobility hubs (eHUBS)

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ABSTRACT

eHUBS are physical locations that integrate two or more electric shared mobility modes. As they provide transport users easier access to a wide range of transport modes, multimodal behaviour is expected to be more common. However, this issue has not been addressed in previous stated preference studies on mode choices involving innovative transport modes. In this study, multi-modal behaviour is explicitly addressed both in measurement and in modelling by adopting the multiple discrete–continuous (MDC) modelling framework in contrast to discrete choice models. Instead of asking transport users to indicate the most preferred alternative, they were allowed to choose more than one alternative by allocating trips between several modes. This study aims to answer two questions: 1) whether there is complementarity between the multiple shared modes offered in eHUBS and 2) how would transport users adapt when one of the shared modes that they plan to use becomes unavailable. Using stated mode choice data of non-commuting trips from transport users whose current mode is driving a private car in Manchester, UK, several models under the MDC framework were estimated including Multiple Discrete-Continuous Extreme Value (MDCEV) model, mixed MDCEV model, and the extended Multiple Discrete Continuous (eMDC) model. The results show that there is complementarity between shared electric vehicle (EV) and electric bike (e-bike) offered in the eHUBS. In addition, the research show that the flexibility between those two shared modes is stronger than assumed in the MDCEV model, and common preference heterogeneity cannot fully account for this phenomenon.

1. Introduction

Recent years have witnessed a rapid growth of emerging transport modes and services such as car sharing, ridesharing, and shared micromobility including bikes, e-bikes, and e-scooters (Liao and Correia, 2022). However, each of these emerging services is unlikely to compete with the functionality of a private car, which severely limits their potential in reducing the negative externalities of road transport (Christensen et al., 2022; Kent, 2014; Moody et al., 2021). To further enhance the ability of these transport innovations in reducing private car ownership and use, there have been some efforts in integrating mobility services from different providers both in terms of online and offline access. For example, Mobility-as-a-Service (MaaS) offers a unified gateway for accessing and paying for different public or private transport services via a smartphone app (Caiati et al., 2020; Ho et al., 2021). Mobility hub is another type of

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mobility integration that has recently gained attention in many cities and regions: they bring together multiple shared mobility services in a single physical location with due attention to public transport services in the vicinity to increase their uptake and provide transport users with better connectivity. eHUBS is one of the pioneering projects in Europe for deploying mobility hubs integrating multiple shared electric modes including electric cars, e-bikes, and e-cargo bikes (Bösehans et al., 2022).

These integration efforts allow easier transfer between modes and facilitate intermodal trips (Kuijk et al., 2022), but this is definitely not the only purpose of these services and systems and many users would still use these services for short and uni-modal trips. Although for each trip only a single mode is used, multiple modes can be chosen at a tactical level when a person is taking a planning perspective for mobility arrangements. For example, instead of committing to a specific shared service, someone may prefer to use shared e-bikes for half of her commuting trips in the entire week and shared electric cars for the other half, which gives an ideal combination of convenience and level of activity. On each trip, transport users will randomly choose a mode to use according to their choice probability regardless of day-specific conditions. Since mobility hubs and MaaS can potentially reduce the cognitive and practical burden to use multiple modes, more people will have easier access to a variety of transport modes which can lead to more multimodal travel behaviour. ***However, this type of behaviour has not been accommodated and analysed in most stated preference studies on mode choice to date, as people were assumed to always choose the same mode under a certain circumstance and different modes are mutually exclusive. This will be the exclusive focus of our paper and intermodal trips are not considered.***

Regarding the demand for the mobility services provided via eHUBS or mobility hubs in general, there are two sets of outstanding questions that can bring valuable insights into the design and operation of the hubs: in the first set, the questions concern the *complementary/substitution* relationships between the multiple mobility services offered in the hubs. Will people use multiple modes in these hubs? Are there synergies between different mobility services, or are they strong substitutes for each other? Is there an added value in providing multiple modes in a hub? The second set mostly concerns people's *flexibility* between different modes. Are people flexible when making choices among these new mobility services? When one of the mobility services in the hub becomes unavailable, would people use other modes and services in the hub as a replacement, or would they fall back to their traditional modes? ***Since mobility hubs are still in their introduction period, there is hardly any previous study shedding light on these questions.***

Given these research gaps, this study aims to contribute to the existing literature in the following ways. Firstly, we model people's mode choice as a multiple discrete variable and capture their multimodal behaviour via a stated choice experiment. This allows to more accurately depict people's real behaviour when eHUBS become available. Secondly, we investigate whether there exists complementarity between the modes offered in the eHUBS. We use two different approaches and models to capture the complementarity/substitution between modes: via correlations between alternatives in the mixed MDCEV model, and via explicit extra terms for the interaction between alternatives in the eMDC model. Thirdly, we explore people's flexibility between the eHUBS modes by investigating their adaptation when an eHUBS mode becomes unavailable. We compare the prediction performance of three models (MDCEV, mixed MDCEV and emergent value model) under different mode availability scenarios to evaluate their capability in capturing people's modal flexibility.

A brief overview of previous literature that is relevant to the topic of our study is provided in section 2. Section 3 presents the design of the stated choice experiment and the details for data collection. Section 4 elaborates upon the modelling approach that is used to answer the research questions. Section 5 discusses our modelling results and their implications. Section 6 is to present the conclusions from research and to give recommendations for future research.

2. Literature review

2.1. Accommodating multimodal behaviour in stated choice experiments

Multimodality refers to the phenomenon that travellers use multiple transport modes for their trips. Most studies on multimodality examine how they use different modes across different circumstances, such as different trip purposes, origins and/or destinations, day of the week, and departure time. However, even for trips that share the same characteristics, multimodality is still detected. For example, a survey in 2008 found that 19 % of MIT employees use multiple modes for their commute trips in a given week . Kuhnimhof (2009) used a one-week travel diary from Germany Mobility Panel and found the percentage of people using different modes for commute and non-commute routines are respectively 28 % and 22 %. Based on data collected from commuters in Bristol and Beijing, Chatterjee et al. (2016) and Mao et al. (2016) both found around 30 % of people were using multiple travel modes for their commuting trips. Heinen et al. (2011) obtained the commute mode choice from 633 cyclists in two Dutch cities for a year (once every two weeks) and found that 49 % of them used modes other than the bike for at least one-third of the trips. Thomas et al. (2019) conducted a smartphone-based survey that automatically registered the trip information of 432 respondents in the Netherlands for four weeks and detected mode choice variation even for repeatedly visited locations. Although it is impossible to know whether these variations in mode choice can be explained by day-specific conditions such as mode availability, weather for example, the previous findings demonstrate that multimodality is a robust behaviour for a significant group of people even for trips under similar or identical circumstances.

As mentioned above, multimodal behaviour may be due to change of circumstances: for example, certain modes may be unavailable at the time of a specific trip; utility of modes can also vary depending on trip contexts (weather conditions, trip purpose) and day-specific considerations such as different needs and activities on different days (Cherchi and Cirillo, 2014; Levinson and Zhu, 2013; Sfeir et al., 2020). This can be addressed by adding context variables in the models. However, we would like to stress that individuals may also have a preference for multimodality even when trip circumstances do not vary. Travellers may be balancing different goals: apart from only exploiting the mode with the highest utility, they also gain from exploration and diversifying (Swait et al., 2013).

Another possible motive is that when travellers encounter repeated choice scenarios and make decisions at a tactical planning level, choosing a combination of different alternatives may provide a bundle/portfolio effect: it allows decision-makers to achieve an optimal mix of level of service, flexibility, and average costs compared to always choosing a single alternative (Tapia et al., 2021).

Despite abundant empirical evidence for this phenomenon, previous mode choice studies involving innovative mobility modes and services hardly accounted for this type of behaviour. That opens up an important research gap in this area of research. The vast majority of studies using stated choice experiments adopt the discrete choice paradigm, which presents mutually exclusive alternatives and the respondent has to choose a single alternative that he/she prefers the most. This implicitly assumes that an individual will always use the same mode under a certain condition described by each choice task. There were only a few stated preference studies that attempted to accommodate choices that involve the use of multiple modes. Sfeir et al. (2020) studied the commute trip mode choice of university students and workers when shared taxi and shuttle services are implemented: respondents were able to choose how many days per week they would be using each offered service. Tapia et al. (2021, 2020) modelled grain consolidators' port and mode choice in the freight transport context: in this experiment respondents can allocate their goods between different transport modes.

2.2. Complementarity and substitution between shared modes

Complementarity and substitution concern the relations between different transport modes. If the demand for a mode increases, the demand for the other mode would increase (or decrease) if there exists complementarity (or substitution) between the two modes. Previous studies examining mode complementarity and substitution mostly focused on the relationship between mobility innovations and existing traditional modes. For example, many studies investigated the relationship between carsharing and existing modes, especially public transit: the findings are mixed as some studies reported carsharing users to have increased their public transport usage while others found a reduction (Becker et al., 2017; Kopp et al., 2015; Le Vine et al., 2014; Papu Carrone et al., 2020). A possible reason is that there are many other factors influencing the net change in public transport use since it depends on individual characteristics, car ownership, and specific features of the carsharing system and public transport services. Many of these results were based on simple descriptive statistics of carsharing users' self-report, while more detailed data and advanced statistical analysis are needed to conclude (Martin and Shaheen, 2016).

Ceccato and Diana (2021) investigated the complementary and substitution pattern between carsharing and other modes on a trip level: for a specific trip in their diary, the respondents indicated their intention to use carsharing to complete the same trip in the future and regression analysis was conducted to explain this intention, including variables such as the modes they used in the past for this trip and their intention to use other modes for this trip in the future. Based on the regression model they made several conclusions, for example, they state that there is a strong complementarity between carsharing and bikesharing because the frequency of bikesharing current usage has a negative effect on the intended future use of carsharing for the specific trip, while the intended future use of bikesharing for the specific trip has a positive impact. They also found evidence for the substitution effect between carsharing and private cars. However, there are two limitations to their approach: first, they only elicited the general intention of usage without considering the performance attributes of different modes; second, the intention of future use of different modes cannot be directly translated into the amount of use.

2.3. Flexibility between modes

There are rather few papers that looked at the topic of modal flexibility. These studies typically consider it as an individual characteristic that denotes the possibility for a person to vary her travel mode. This construct was operationalized as the self-reported number of modes a respondent considers feasible to use (Lavery et al., 2013) or their perceived ability to vary transport modes (Mao et al., 2016). However, flexibility can also represent a type of relationship between two modes beyond complementarity/substitution: when one mode becomes unavailable, to what extent would the remaining available modes serve as replacements? Multiple-Discrete choice models have implicit assumptions regarding the patterns of replacement: for example, the consumption of remaining alternatives will increase proportionately in the case of the MDCEV model, but this may not be true and can result in bias in mode use prediction when some modes become unavailable. To the best of the authors' knowledge, there is no previous research studying how people adapt their choices when the availability of mobility services changes, especially in a multimodal context. This topic is of extreme importance under a scenario of greater usage of shared modes (on-demand intermittent supply) in which they are integrated into the same physical space as it happens with the eHUBS.

3. Survey design and data collection

3.1. Stated choice experiment design

A survey that includes a stated choice experiment was designed to capture transport users' mode choice behaviour when eHUBS become available. These eHUBS offer one-way shared mobility services where shared vehicles are assumed to be always available. An introduction to eHUBS is provided before the experiment to ensure that all respondents were familiar with the basic operation of eHUBS (see details in Appendix 1).

Both commuting and non-commuting experiments were carried out in this survey. Since we focus on the topic of complementarity and flexibility in this paper, a single dataset is considered to be sufficient to do the analyses. With that in mind we selected the data from the non-commuting experiment since all respondents participated in this experiment while the commuting experiment was only completed by people who commute at least two times a week. Six trip contexts are included to cover different combinations of distances (1,3,6 miles) and purposes (leisure and shopping).

Instead of having all viable transport modes as alternatives in each choice task, only three alternatives were included: the current mode used by the respondent for the specific trip context, shared EV and shared e-bike (or shared e-cargo bike in case of a shopping trip) in an eHUB. For the current mode, the respondents can choose from ten options, including driving a private car, being a passenger on a private car, public transport, walking, private bike, private e-bike, carsharing, bikesharing, taxi, and motorbike. The e-cargo bike is only available for the shopping purpose, whilst the e-bike is available for the leisure purpose. Therefore the "current mode" alternative is respondent- and trip-specific (a respondent may use different modes for trips of varying distances and purposes). This approach is similar to stated adaptation experiments designed before (Langbroek et al., 2017; Pan et al., 2019). Here the focus is to explore to what extent people would use eHUBS to replace the mode they are currently using. Since stated choice experiments require respondents to state their behaviour under hypothetical scenarios, this may lead to bias in responses compared to their behaviour in reality (Fifer et al., 2014). In our case although the two shared modes may not yet be available for many respondents, the vehicles involved – cars and e-bikes – are both quite common and shall not cause strong deviation from real preference; we also carefully explained the procedure of using a shared vehicle in detail before the experiment.

The attributes in the experiment include the most common ones in mode choices such as travel time, travel cost, and access time. We also investigated congestion level as this was found in previous studies to be influential in mode choice (Krueger et al., 2019). As potential policy levers, parking time and cost were included to explore their impact on diverting people away from using private car. All attributes are varied by three levels: their value and range are based on other currently available services and what can be plausible in the near future. Table 1 presents the levels of each attribute. When specifying attribute levels, we aimed at reducing hypothetical bias to the extent possible by ensuring that all attribute values fall within realistic ranges: we referred to similar stated preference studies on mode choice (Arentze and Molin, 2013; Li and Kamargianni, 2020, 2018; Papu Carrone et al., 2020), checked current and possible future regulations (for example, the e-bike speed limit in UK is currently around 15 mph and there was petition to raise it to 20 mph) and also information of shared mobility services currently in operation in Europe. This ensures that all alternatives can be easily imagined by the respondents.

Efficient designs can be used to increase the statistical efficiency of estimates; however, Walker et al. (2018) found that efficient design is less robust than orthogonal design, in the sense that it becomes less efficient when the true coefficient value is very different from the prior used in design generation. Since our experiment involves innovative modes and we cannot easily obtain reliable priors for its attribute coefficients, we decided to use an orthogonal design. An orthogonal design with 27 choice tasks was generated. Each respondent received six choice tasks in total: they were presented with all six trip contexts and one choice task per context. The six choice tasks per respondent were randomly drawn without replacement from the orthogonal design and then randomly paired with the six contexts. Fig. 1 shows an example of a choice task (with the paired context).

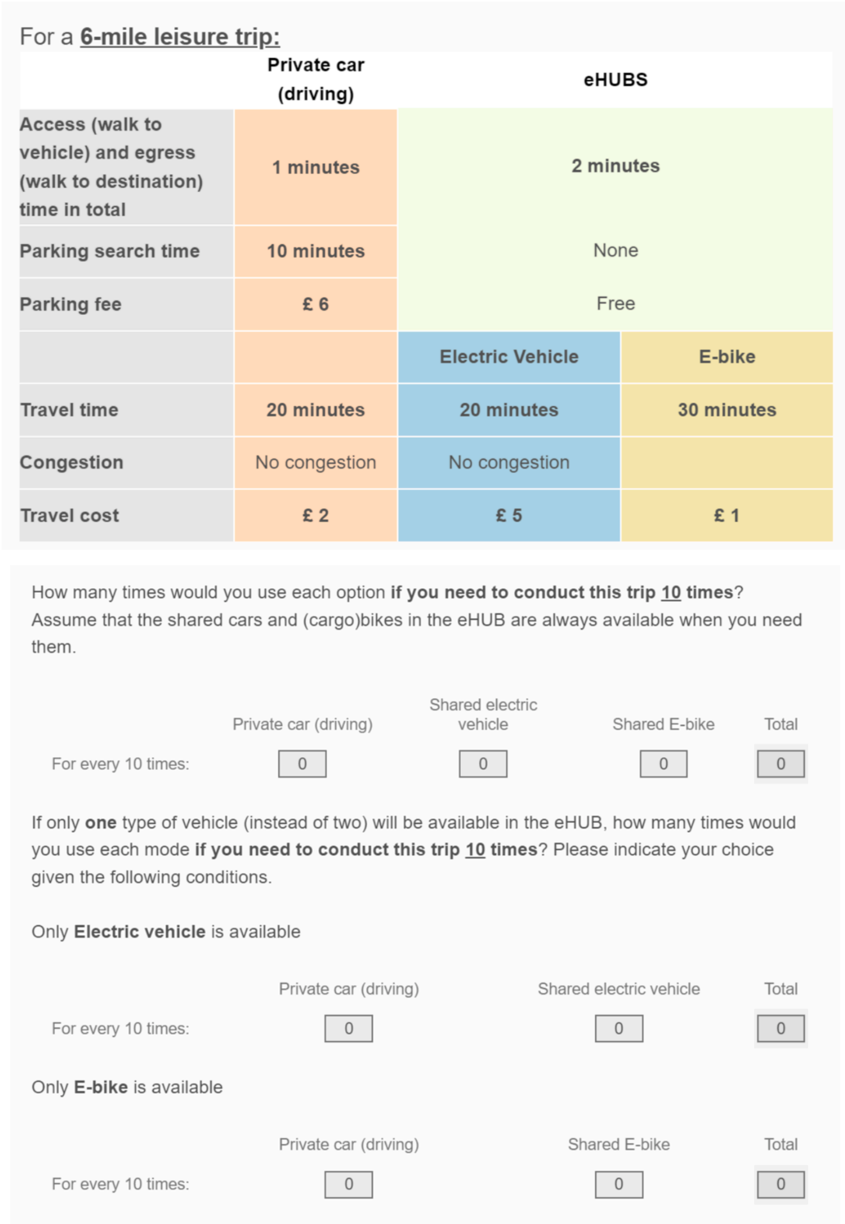
The questions in each choice task are different from the standard choice question. Instead of asking respondents to indicate only their most preferred alternative and assuming they will always use this alternative, their multimodal behaviour was accommodated by allowing respondents to choose multiple alternatives:

Q1*: How many times would you use each option if you need to conduct this trip 10 times?*

Our aim is to elicit the percentage of trips allocated to each mode. We could have directly elicited the percentage of each alternative (Blass et al., 2010; Tapia et al., 2021) such as "I use private car 50 % of the time and shared e-bike 50 % of the time", but the concept of probability may be less straightforward to understand for some respondents. The reason why we ask respondents to answer assuming a total of 10 trips is because 1) it is a sufficiently large number and we can obtain percentages/probabilities that are of sufficient precision and 2) it is easier to calculate compared to asking people to answer based on their actual total number of trips per month or year. This type of question has already been applied in previous mode choice studies (Sfeir et al., 2020). In model estimation, we scaled

Table 1
Attribute values of the non-commuting experiment.

Attributes	Private car	eHUB	
Access and egress time	Access: elicited from respondent Egress: 1 mile: 1,3,5 min 3 mile: 1,5,9 min 6 mile: 1,5,9 min	 1 mile: 2,6,10 min 3 mile: 2,10,18 min 6 mile: 2,10,18 min	
		EV	**E-bike (E-cargo bike for the shopping purpose)**
Travel time	Same as shared EV	1 mile: 3, 5, 7 min 3 mile: 7, 10, 13 min 6 mile: 15, 20, 25 min	1 mile: 4, 6, 8 min 3 mile: 10, 12, 14 min 6 mile: 20, 25, 30 min
Travel cost	£0.1, 0.2, 0.3/km (1,3,6 mile as 2, 5, 10 km)	£0.15, 0.25, 0.35/min	£0.5, 1.0, 1.5 (regardless of distance)
Congestion level	Same as shared EV	Chance of delay: 0 %, 20 %, 40 % Possible delay: 25 %, 50 %, 75 % of travel time	
Parking search time	0, 5, 10 min		
Parking fee	£0, 3, 6		



For a **6-mile leisure trip:**

	Private car (driving)	eHUBS	
Access (walk to vehicle) and egress (walk to destination) time in total	1 minutes	2 minutes	
Parking search time	10 minutes	None	
Parking fee	£ 6	Free	
		Electric Vehicle	E-bike
Travel time	20 minutes	20 minutes	30 minutes
Congestion	No congestion	No congestion	
Travel cost	£ 2	£ 5	£ 1

How many times would you use each option **if you need to conduct this trip 10 times**? Assume that the shared cars and (cargo)bikes in the eHUB are always available when you need them.

	Private car (driving)	Shared electric vehicle	Shared E-bike	Total
For every 10 times:	0	0	0	0

If only **one** type of vehicle (instead of two) will be available in the eHUB, how many times would you use each mode **if you need to conduct this trip 10 times**? Please indicate your choice given the following conditions.

Only **Electric vehicle** is available

	Private car (driving)	Shared electric vehicle	Total
For every 10 times:	0	0	0

Only **E-bike** is available

	Private car (driving)	Shared E-bike	Total
For every 10 times:	0	0	0

Fig. 1. Example of a choice task.

all responses into probabilities (e.g. "using private car for 7 out of 10 trips" equals to "using private car 70 % of the time"): this implies that the outcome of our model is the probability or fraction assigned to each mode and it does not pose a restriction on the total number of trips.

In order to investigate transport users' flexibility to choose between the two shared modes when one of them becomes unavailable, choice adaption behaviour was elicited by asking the following questions:

***Q2**: If only one type of vehicle (instead of two) will be available in the eHUB, how many times would you use each mode if you needed to conduct this trip 10 times?*

- *Q2.1 Please indicate your choice when only a shared EV is available.*
- *Q2.2 Please indicate your choice when only a shared e-bike is available.*

3.2. Data collection and sample characteristics

The questionnaire was distributed online among adults who hold a driver's license and live in Manchester, United Kingdom. Survey distribution was conducted by collaborating with a panel set by a market research company in March 2021 with an aim of 1000 respondents. After excluding respondents with a completion time shorter than 5 min (given our survey length it is not possible to finish within 5 min), the final sample has 973 valid respondents. In this paper, only choice tasks in which the current mode is driving a private car were analysed because they take the largest share (60.8 %) in the sample; a specific interest is also taken to this group since one of the main goals of eHUBS is to take transport users away from private car, both their use and ownership. Therefore, 154 respondents who do not currently use a private car for any non-commuting trips were excluded. In total 819 respondents and 3551 choice responses (not everyone uses the car for all non-commuting trips and the number of choice responses from each respondent differs) were used in the analysis. Table 2 presents an overview of the socio-demographic variables distribution of the sample in this study. Since we cannot find the statistics for the specific population, we list the statistics for Manchester's general population instead. Although it is hard to evaluate the level of representativeness, we can see that the sample achieved a good combination from all demographic groups. For a summary of choice responses such as number of respondents choosing each mode (or their combinations) and the average days allocated to each alternative, readers can refer to the first column of Table 5 and 6.

4. Modelling approach

4.1. MDCEV model

Given the multiple-discreteness of the choice data in this study, it is a natural choice to adopt the state-of-the-art modelling framework – Multiple Discrete-Continuous Extreme Value (MDCEV) model (Bhat, 2008, 2005). Given a fixed budget, the model describes both the discrete choices (which alternatives are chosen) and the continuous consumption amount (how much of each alternative is consumed). The model assumes that an individual chooses a certain amount of each alternative to maximize the utility function as follows:

$$U(\boldsymbol{x}) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k}\psi_k\left\{\left(\frac{x_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right\}$$

$$s.t.\sum_{k=1}^{K} x_k = B \tag{1}$$

In which $\psi_k = e^{\beta_k z_k + \varepsilon_k}$, z_k is the vector of attribute values associated with mode k (and socio-demographic variables), x_k is the amount allocated to each chosen alternative, K is the total number of available alternatives, M is the number of chosen alternatives, B is the budget, β_k is the vector of attribute coefficients, and α_k and γ_k are satiation parameters. The value of γ_k has to be larger than zero. In our case, x_k is scaled to the probability or fraction allocated to each mode and the budget of all choice situations is 1.

It has a closed-form likelihood function as follows, which is convenient for estimation:

$$LL = \frac{1}{\sigma^{M-1}} * \left[\prod_{i=1}^{M} c_i\right] * \left[\prod_{i=1}^{M} \frac{1}{c_i}\right] * \left[\frac{\prod_{i=1}^{M} e^{\frac{V_i}{\sigma}}}{\left(\sum_{k=1}^{K} e^{\frac{V_k}{\sigma}}\right)^{M}}\right] * (M-1)! \tag{2}$$

In which $V_k = \beta_k z_k + (\alpha_k - 1)\ln\left(\frac{x_k}{\gamma_k}+1\right)$, $c_i = \frac{1-\alpha_i}{x_i+\gamma_i}$ and σ is the scale parameter of the error term.

The MDCEV model was originally proposed under the "horizontal" principle, meaning that the choice of selecting multiple alternatives is done simultaneously (Bhat, 2005). Mode choices can be argued as violating the "horizontal" principle since only a single mode (or mode chain) can be used in each trip and the multiple-discreteness can only be manifested over repeated discrete choices correlated through a budget constraint (Tapia et al., 2021). However, there have been many empirical applications of the MDCEV model under similar contexts such as time use, frequency of mode use, and car mileage, which are strictly speaking all repeated discrete choices (Bhaduri et al., 2020; Calastri et al., 2017; Jäggi et al., 2013). The model can thus be considered agnostic toward the specific decision-making process. Moreover, as it was mentioned earlier, it is also plausible that people would take a tactical planning view regarding their mobility arrangements for a long period, which would be satisfying the horizontal condition.

Since no alternative was chosen in all choice tasks, the basic MDCEV model and the two mixed MDCEV models introduced in the next section are all estimated using the structure without an outside good. Since α and γ in MDCEV are confounded and cannot be simultaneously identified, the γ −profile was adopted by fixing alpha (α) to zero and only estimating gamma (γ) for each alternative. Although the γ −profile theoretically allows the identification of the scale parameter, in this study it showed a high correlation with several β and γ parameters. Therefore the scale parameter was fixed to 1 as has been done in some previous studies (e.g. Pudāne et al., 2021).

4.2. Complementarity: Mixed MDCEV and eMDC

The meaning of complementarity is first clarified here. The traditional Hicksian complementarity means that when the demand for

Table 2
Sample characteristics.

Variable	Value	Percentage among sample (people using car for non-commuting trips, N = 819)	Percentage among Manchester population
Gender	Female	60.4 %	50.7 % [a]
	Male	39.6 %	49.3 % [a]
Age	18–24	8.7 %	19.9 %[a]
	25–34	28.3 %	23.6 % [a]
	35–44	26.0 %	25.6 % [a]
	45 or older	37.0 %	30.9 % [a]
Education	No higher education	36.5 %	62.4 %[b]
	With higher education	63.5 %	37.6 %[b]
Household Income	Low (<=£40 k)	46.5 %	/[c]
	Middle (>£40 k and <=£80 k)	44.3 %	/[c]
	High (>£80 k)	9.2 %	/[c]
	Missing value	4.3 %	/[c]
Occupation	Employed	75.0 %	50.2 %[b]
	Student	5.6 %	18.1 %[b]
	Others	19.4 %	27.7 %[b]
Number of children	0	56.3 %	69.8 %[d]
	1	18.8 %	30.2 %[d]
	More than 1	24.9 %	
Cars in household	0	/	/
	1	43.3 %	70.5 %[e]
	More than 1	56.7 %	29.5 %[e]

Note: a. among adult population. b. among people aged 16 years and over. c. Cannot find corresponding categories. d. among all households. e. among households with cars.
Source of population statistics: Office for National Statistics (ONS).

one item increases, the demand for the other item also increases (Hicks and Allen, 1934). In the context of multiple discrete–continuous choices with a fixed budget, there are two things worth mentioning when discussing complementarity/substitution:

First, the budget constraint already indirectly induces substitution between alternatives; therefore, even if two alternatives are complementary, increasing demand for one of them would not necessarily lead to an increased demand for the other, since the net change in demand also depends on the indirect substitution imposed by the budget. The complementarity can also be identified for products with negatively correlated demand as described in Palma and Hess (2022).

Second, "complementarity" in discrete choices does not necessarily imply complementarity in terms of the continuous amount of consumption. Intuitively complementary products are products that "go together" (Manzini et al., 2019); when illustrating the concept of complementarity, examples such as "products that are usually bought together" (Palma and Hess, 2022). However, "two products being chosen together" is only a phenomenon in the aspect of discrete choices, it does not necessarily mean that the two products are also complementary in terms of continuous consumption. Consider the MDCNEV model (Pinjari and Bhat, 2010): when two alternatives belong to the same nest, they will also "go together" and be chosen simultaneously more often (Hernandez et al., 2023); but instead of being complements, the rate of substitution in terms of continuous consumption is even higher between the alternatives within the same nest (Pinjari and Bhat, 2010).

There are two approaches for incorporating complementarities and substitutions in multiple-discrete continuous models. The first is to allow correlations between different alternatives, for example estimating a mixed MDCEV model incorporating a common random error component for the alternatives which are supposedly related (Calastri et al., 2020). The utility of shared modes can thus be written as follows:

$$\psi_k = e^{\beta_k z_k + \vartheta_k + \vartheta_{Shared} + \varepsilon_k} \tag{3}$$

$$V_k = \beta_k z_k + (\alpha_k - 1)\ln\left(\frac{x_k}{\gamma_k} + 1\right) + \vartheta_k + \vartheta_{Shared} \tag{4}$$

In which ϑ_{Shared} is a common error component in all shared modes (in our case both shared EV and shared e-bike) and captures the correlation between these alternatives, and ϑ_k is an alternative-specific error term. All error components are independently and identically distributed (with zero mean normal distribution) across respondents, with their standard deviation to be estimated.

The log-likelihood function would then become:

$$LL(mixed) = \int \prod_{t=1}^{T} Likelihood(\vartheta) f(\vartheta) d\vartheta \tag{5}$$

In which T denotes the number of choice tasks of each individual: error terms are individual specific which capture the correlation in panel data.[1]

The caveat of this approach is that the source of the correlation is unclear: it can be due to common heterogeneity, complementarity, or substitution (Calastri et al., 2020). To disentangle the source of correlation and identify genuine complementarity/substitution, a second approach can be applied by using non-additive utility formulations to incorporate explicit interactions between different alternatives. The additive utility function (1) can be taken forward as the basis and then add multiplicative terms to it to incorporate interactions between pairs of alternatives. There have been multiple models incorporating complementarity/substitution via non-additive separable utility functions (Bhat et al., 2015; Pellegrini et al., 2021); However, a drawback of these formulations is that they are only valid for some values of the complementarity/substitution parameters, which can lead to both difficulties in estimation and forecasting (Calastri et al. 2020; Palma and Hess 2022). To be more specific, the marginal utility of any good at any consumption point for each good $\frac{\partial U}{\partial x_k}$ should always be positive. However, in these model formulations, $\frac{\partial U}{\partial x_k}$ depends on the level of consumption of each individual, indicating that a model's correctness can only be evaluated for each specific dataset which hinders model transferability and forecasting. Moreover, extra effort is needed during model estimation to prevent the algorithm from testing parameter combinations violating $\frac{\partial U}{\partial x_k} > 0$. The readers can refer to Palma and Hess (2022) for more details regarding the potential drawbacks of Bhat et al. (2015) and other MDC models.

A recently proposed model is used here – the extended Multiple Discrete Continuous (eMDC) model (Palma and Hess, 2022) – to explicitly incorporate complementarity and substitution between alternatives. This model does not impose constraints on parameters and is computationally tractable. The utility function is as follows:

$$U(\boldsymbol{x}) = u_0(x_0) + \sum_{k=1}^{K} u_k(x_k) + \sum_{k=1}^{K-1}\sum_{l=k+1}^{K} u_{kl}(x_k, x_l) s.t. \sum_{k=0}^{K} x_k = B \tag{6}$$

In which

$$u_0(x_0) = \psi_0 \log(x_0) \tag{7}$$

$$u_k(x_k) = \psi_k \gamma_k \log(\frac{x_k}{\gamma_k} + 1) \tag{8}$$

$$u_{kl}(x_k, x_l) = \delta_{kl}(1 - e^{-x_k})(1 - e^{-x_l}) \tag{9}$$

$$\psi_0 = 1 \tag{10}$$

$$\psi_k = e^{\beta_k z_k + \varepsilon_k} \tag{11}$$

Most notations in equation (6) are identical to MDCEV. The main noticeable differences include: 1) it explicitly includes multiplicative terms $u_{kl}(x_k, x_l)$ which represent the interaction between different alternatives with a set of δ_{kl} coefficients to be estimated. If $\delta_{kl} > 0$ ($\delta_{kl} < 0$), there is complementarity (substitution) between alternatives k and l since $u_{kl}(x_k, x_l)$ will increase (decrease) when the consumption of x_k and x_l increases; 2) $u_k(x_k)$ takes the functional form of the γ-profile of MDCEV by assuming $\alpha \to 0$; 3) it assumes an outside good x_0 which is always chosen; 4) the marginal utility of the outside good ψ_0 does not contain a stochastic error term (and is fixed to 1 in this study).

Although using stochastic errors following the Gumbel distribution can result in a closed-form likelihood, it was found to generate a high number of outliers in prediction due to its thick tail; eMDC is therefore implemented with normally distributed errors. Moreover, unlike MDCEV, the determinant of the Jacobian term in the likelihood function for eMDC does not have a compact form. Due to these reasons, the likelihood function will not be reproduced here. Forecasts based on eMDC can be done by applying algorithms capable of handling nonlinear objective functions and both equality and inequality constraints, which are incorporated in off-the-shelf packages such as Rsolnp (Ghalanos A, 2015). More details on the model are available in a recent publication by Palma and Hess (2022).

From equation 9) we can see that the size of δ parameters depends on the scale of consumption: since the value of $(1 - e^{-x_k})(1 - e^{-x_l})$ is rather sensitive to the values of x_k and x_l when they vary from 0 to 1 (compared to when they are between 0 and 10), we encountered optimization difficulties when we estimate the model with responses scaled to probability. Therefore, we used the original response data (number of trips using each mode out of 10 trips) in the estimation of the eMDC model.

The eMDC modelling framework also requires an outside good that is always chosen/consumed; however, none of the three alternatives in our stated choice experiment was chosen in all choice tasks at least for one day. To still apply the model, the strategy in Palma and Hess (2022) is followed by setting the budget to be 10.1 and assuming an outside alternative which is always assigned 0. 1. Although this assumption is rather arbitrary and would inevitably hamper its prediction performance compared to the models which do not require an outside alternative, it shall not affect the relations between the "inside" alternatives and our objective of diagnosing complementarity and substitution relations between the shared modes. We also tested this by estimating the model with a wide range

[1] Note that this formulation only allows for a positive correlation between these two alternatives. A mixed MDCEV model was also estimated that allows for negative correlation and the correlation turned out to be positive. The error structure in the final mixed MDCEV model is adopted since the coefficients can be interpreted in a straightforward manner.

of values for the amount of outside good: the sign and statistical significance of δ parameters remain robust, which empirically shows that this imposed assumption does not affect our conclusion regarding the complementarity and substitution between alternatives.

Compared to the MDCEV models, the utility functions for all three modes were modified due to the imposed outside good. We have three trip distances (1, 3 and 6 mile) in our dataset and the travel time of all modes is roughly proportionate to the distance: for example, the travel time of a 6 mile trip is around two times the travel time of a 3 mile trip. Therefore, if the travel time-related utility is formulated as $\beta_{traveltime}*\textit{traveltime}$, the utility of all three alternatives would decrease when the trip distance is longer. Given that the utility of the outside good is fixed to 0, this implies that the consumption of the outside good would increase in longer trips; but this value is fixed to 0.1 in all choice observations and it can lead to confounded travel time parameter estimates. To mitigate this impact, the trip distance shall not have such a "scaling" effect on utilities via attributes. Instead of directly using the absolute value of travel time in the utility function, we recode it as the value difference from the middle level of travel time: for example, the travel time of shared e-bike can take 20, 25 or 30 min for a 6 mile trip; in our scheme, they would be recoded to −5, 0, and 5. We also allow ASCs to be different for each distance.

Regarding the scale parameter (standard deviation of the stochastic error term), it was estimated simultaneously with other parameters in the eMDC model at first but we encountered difficulties in the estimation. Then we attempted estimation by fixing the scale parameter to different values: when it took a smaller value the RMSE of the aggregate prediction would be slightly better, while all coefficient estimates were generally scaled accordingly and there was no significant change in terms of their statistical significance. This indicates that its value hardly has any influence on our purpose with estimating the eMDC model, which is identifying the existence of complementarity and substitution. The final model was estimated with this parameter fixed to 1.

4.3. Flexibility: Mixed MDCEV and emergent value model

By contrasting the responses between Q1 and Q2 and observing how people adapt when a shared mode they would like to use becomes unavailable, insights regarding transport users' flexibility between the two shared modes can be obtained.

According to the IIA assumption in MDCEV, when an alternative becomes unavailable, the continuous consumption of the remaining alternatives will increase proportionately. However, as it is seen later in the results section when one of the shared modes becomes unavailable, the usage of the remaining shared modes will increase more than the MDCEV predicts, suggesting that the flexibility between the two modes is stronger than the model assumes.

The first possible reason for this phenomenon is similarity and common preference heterogeneity: since two shared modes are more similar, when one of the shared modes becomes unavailable, the remaining shared mode will serve as a better replacement, hence its consumption will increase by a greater proportion compared to the private car. This will be explored with mixed MDCEV which can accommodate correlation between alternatives due to common preference heterogeneity.

A second possibility is an ad-hoc approach called emergent value (Guevara and Fukushi, 2016): it assumes that the utility of alternatives can change when the choice context (e.g. available alternatives) changes. In this study, the emergent value of shared EVs and e-bikes when the other shared mode is unavailable will be examined. The marginal utility function for this study is proposed as follows:

$$\psi_k = e^{\beta_k z_k + EV_k * 1(AV_l = 0) + \varepsilon} \tag{6}$$

In which EV_k is the emergent value of alternative k when the alternative l is unavailable, $1(AV_l = 0)$ is an indicator variable that takes the value 1 when l is unavailable and 0 otherwise. Its functional form can accommodate any level of flexibility between shared modes, but it is agnostic towards the underlying behavioural mechanism and runs the risk of overfitting. Its prediction performance compared to the mixed MDCEV model will be examined.

Our focus is evaluating the prediction performance of different models, especially in terms of how they predict people's adaptation under different mode availability. A base forecast which predicts using the original sample is considered first and see how well it can recover the original sample statistics. The root mean squared error (RMSE) of the aggregate predictions is used as the indicator of forecast error (Palma et al., 2021; Palma and Hess, 2022); this metric is calculated separately for each mode availability context (Q1, Q2.1 and Q2.2). We first check whether the model estimated only using responses for Q1 can generate accurate prediction when one of the eHUBS modes becomes unavailable. We will test both MDCEV and mixed MDCEV model. The next step is to explore whether models estimated with all data (Q1 and Q2) perform better: in this step we examine three models, namely MDCEV, mixed MDCEV and emergent value model.

The second scenario investigated is unconditional prediction where the models forecast the behaviour of new individuals without any information about their choices in the estimation set: a 10-fold cross-validation for the three models was carried out to examine their prediction performance for new data. Each model was estimated using 90 % of the full sample and use the estimated parameters to examine its prediction performance on the remaining 10 % of the sample. All choices made by an individual are in the same subset, which prevents choices of the same individual from appearing in both the training and validation data (Hillel, 2020). This ensures that the prediction is done unconditionally without any information about other choices made by the individuals in the validation set. Apart from the root mean squared error (RMSE) of the aggregate continuous consumption and discrete choice predictions, the RMSE of each choice observation which reflects the average performance for each choice occurrence was also examined: the average RMSE for each alternative (when there are only two alternatives, the RMSE of the two alternatives are identical) was calculated. All values are the average of the 10 repetitions.

5. Results

5.1. Complementarity

The analysis of complementarity between eHUBS modes focused on the responses for Q1, because these choices are made when both eHUBS modes are available. 24 % of the choice observations included more than a single alternative and 47 % of the respondents chose more than one alternative in at least one of the choice tasks, showing that multimodality is a common behaviour. All models were estimated using the Apollo package.

A MDCEV was estimated as the base model. The result is presented in Table 3: The analysis shows that most attribute coefficients are statistically significant; their relative size and the implied value of time also lie within a plausible range. For example, the value of travel time of shared e-bike has a value of around 5 lb per hour, and the access time is valued slightly higher. For comparison, a recent study conducted in Great Britain recommend using 5.12 lb per hour as the value of time for non-work trips (Batley et al., 2019). Results and implications concerning attribute coefficients will not be interpreted in detail in our paper, because our main goal is identifying complementarity and substitution between alternatives instead of obtaining accurate estimates of value of time.

We also incorporated socio-demographic variables to investigate observable heterogeneity. All variables with t-values above 1.2 were retained in the final model. We found that people with higher education are more likely to choose shared EV, while people who are male, younger than 35 years old, or with children are more likely to choose shared e-bike. These findings in general fit the typical image of early adopters of transport innovations.

As for the satiation parameters γ, we can see that the values of shared EV and e-bike are of similar magnitude (the difference is statistically non-significant). The satiation parameter of the private car has a larger value which denotes a lower level of satiation,

Table 3
Parameter estimates of MDCEV models.

	MDCEV		Mixed MDCEV	
	Estimate	t-ratio	Estimate	t-ratio
Car				
ASC	0	/	0	/
Access time	*−0.016*	*−1.609*	**−0.042**	**−3.068**
Travel time	*−0.020*	*−1.637*	−0.014	−0.901
Travel cost	**−0.129**	**−2.375**	**−0.319**	**−4.634**
Parking time	−0.011	−1.260	**−0.023**	**−2.046**
Parking cost	**−0.148**	**−9.593**	**−0.276**	**−12.717**
Congestion probability * time	−0.418	−0.932	−0.625	−1.032
Shared EV				
ASC**	**−0.914**	**−4.224**	**−2.380**	**−7.423**
Young	/	/	*0.385*	*1.868*
High education	**0.262**	**1.984**	**0.453**	**2.090**
High income	/	/	0.545	1.561
Shopping trip	−0.038	−0.493	**−0.218**	**−2.093**
Access time	**−0.042**	**−5.418**	**−0.068**	**−7.255**
Travel time	**−0.065**	**−5.032**	**−0.104**	**−6.337**
Unit travel cost per minute	**−3.049**	**−6.276**	**−3.842**	**−6.350**
Congestion probability * time	−0.223	−0.424	−0.207	−0.313
Shared e-bike				
ASC**	**−1.968**	**−8.444**	**−4.034**	**−9.271**
Male	**0.338**	**2.638**	**0.567**	**2.776**
Young	**0.251**	**1.988**	**0.557**	**2.320**
High education	/	/	0.383	1.514
High income	/	/	**0.775**	**1.950**
Low income	/	/	0.306	1.434
Have children	**0.359**	**2.860**	**0.635**	**3.141**
Shopping trip	**−0.523**	**−6.701**	**−0.984**	**−8.677**
Access time	**−0.029**	**−3.780**	**−0.054**	**−5.560**
Travel time	**−0.024**	**−2.419**	**−0.053**	**−4.103**
Travel cost	**−0.275**	**−2.625**	**−0.530**	**−3.844**
γ: Car	**1.808**	**5.369**	**0.524**	**7.808**
γ: Shared EV	**0.582**	**12.140**	**0.431**	**10.137**
γ: Shared e-bike	**0.660**	**10.495**	**0.403**	**9.198**
σ: Shared EV			**0.651**	**3.437**
σ: Shared e-bike			**1.741**	**12.123**
σ: eHUBS modes			**2.169**	**19.240**
Number of individuals		819		819
Number of observations		3551		3551
LL		−4103.4		−3504.0

** Estimate of mean in mixed MDCEV.
Bold: statistically significant at 0.05 level. *Italic*: statistically significant at 0.1 level.

meaning that it will be used proportionately more than eHUBS alternatives if it is chosen.

As mentioned earlier in the methodology section, in order to accommodate possible complementarity between the two shared modes in eHUBS, we estimated a mixed MDCEV model which allows for both unobserved heterogeneity and correlation between alternatives. It was estimated with 500 MLHS draws: we tested with 1000 draws but ended up with similar results, indicating that 500 draws is sufficient. As per Table 3, the standard deviation of both alternative-specific error components (σ: Shared EV and σ: Shared e-bike) is statistically significant, demonstrating that there is unobserved heterogeneity in the preferences for these two modes of shared EV and shared e-bike. Most importantly, the standard deviation for the common error component shared by the two eHUBS modes (σ: eHUBS modes) is also statistically significant, indicating that there is correlation between these two modes. However, the study cannot conclude that there exists complementarity between the two eHUBS modes based on the results of mixed MDCEV only, since this correlation can also be a result of common heterogeneity in preferences.

In order to disentangle the source of correlation and identify whether it is due to complementarity, we estimated an eMDC model and the results are presented in Table 4. As discussed earlier, the δ parameter estimates denote the complementarity/substitution relations between alternatives. The δ parameter between shared EV and e-bike is positive and statistically significant; this indicates that these two alternatives are complementary. The results also show that there is substitution between private car and the two eHUBS modes. Given the 66 % share of respondents who chose to completely stick to the car, this is not surprising. As for attribute coefficients, all significant coefficients have the expected sign; we will not interpret them in detail as they are not our focus. Table 4 also rpesented a

Table 4
Parameter estimates of eMDC models.

	eMDC		**Mixed eMDC**	
	Estimate	**t-ratio**	**Estimate**	**t-ratio**
Car				
ASC*	**3.396**	**57.497**	**3.302**	**54.474**
+ ASC_3mile**	0.020	0.879	0.020	0.910
+ ASC_6mile	**0.062**	**2.681**	**0.060**	**2.715**
Access time	−0.003	−1.113	−0.003	−1.134
Travel time	0.002	0.615	0.002	0.636
Unit travel cost	**−0.322**	**−3.248**	**−0.308**	**−3.228**
Parking time	**−0.007**	**−3.029**	**−0.006**	**−3.022**
Parking cost	**−0.041**	**−10.758**	**−0.040**	**−10.600**
Congestion probability * time	*−0.160*	*−1.852*	*−0.154*	*−1.847*
Shared EV				
ASC	**1.988**	**20.522**	**1.978**	**18.909**
Higher education	**0.155**	**2.436**	**0.185**	**2.527**
+ ASC_3mile	*−0.085*	*−1.811*	**−0.150**	**−2.912**
+ ASC_6mile	**−0.228**	**−4.440**	**−0.322**	**−5.681**
Shopping trip	0.042	1.155	0.007	0.177
Access time	**−0.017**	**−4.644**	**−0.021**	**−5.241**
Travel time	**−0.030**	**−4.436**	**−0.036**	**−4.797**
Unit travel cost per minute	**−1.535**	**−6.311**	**−1.652**	**−6.245**
Congestion probability * time	0.014	0.072	0.042	0.191
Shared e-bike				
ASC	**1.497**	**15.292**	**1.343**	**10.850**
Male	**0.159**	**2.596**	**0.197**	**2.718**
Young	**0.126**	**2.078**	*0.137*	*1.904*
Higher education	/	/	**0.206**	**2.477**
Have children	**0.177**	**2.928**	**0.229**	**3.187**
+ ASC_3mile	**0.176**	**3.355**	**0.141**	**2.450**
+ ASC_6mile	**0.145**	**2.551**	0.089	1.419
Shopping trip	**−0.240**	**−6.599**	**−0.311**	**−7.712**
Access time	**−0.009**	**−2.690**	**−0.013**	**−3.618**
Travel time	−0.003	−0.353	−0.007	−0.948
Travel cost	**−0.149**	**−3.038**	**−0.186**	**−3.564**
γ: Car	**4.681**	**14.076**	**5.418**	**12.665**
γ: Shared EV	**13.117**	**9.827**	**10.128**	**9.769**
γ: Shared e-bike	**14.313**	**8.567**	**20.888**	**4.078**
Higher education			**−13.040**	**−2.574**
δ: Car – EV	**−2.761**	**−10.269**	**−2.297**	**−7.743**
δ: Car – e-bike	**−2.529**	**−10.025**	**−2.279**	**−8.218**
δ: EV – e-bike	**3.472**	**14.211**	**2.284**	**8.456**
σ: eHUBS modes			**0.527**	**15.041**
Number of individuals		819		819
Number of observations		3551		3551
LL		−680.1		−582.8

***:** The ASC of the outside good is fixed to 0.
****:** The base value of car ASC is for 1 mile trips; the value of car ASC for 3 mile trips is (ASC + ASC_3mile). This also applies to other alternatives and distances.
Bold: statistically significant at 0.05 level. *Italic*: statistically significant at 0.1 level.

mixed eMDC incorporating correlation between the two eHUBS alternatives and also satiation parameter heterogeneity. We can see that the standard deviation for the error component shared by the two eHUBS modes (σ: eHUBS modes) is also statistically significant, while the δ parameter between shared EV and e-bike is still statistically significant but smaller in size; this seems to suggest that both complementarity and common heterogeneity in preferences are at play. As for the deterministic heterogeneity of the satiation parameters, only one demographic variable turns out to be significant.

The different implications of these model estimates can be more straightforwardly illustrated in terms of prediction. Table 5 shows the prediction of the three models above using the original sample data. The results consist of two parts: the first part "continuous consumption" reports the average number of trips allocated to each mode when each respondent conducts 10 trips in total across the sample; the outcome of MDCEV models is calculated by the predicted probability assigned to each mode multiplied by 10 (the assumed total number of trips in this table). the second part shows the prediction of discrete choices, namely the share of people in the sample who choose each mode (regardless of the number of trips they allocate to this mode as long as it is more than zero). The column "original data" lists the actual values of the original sample. Note that since the eMDC model assumes an artificially outside alternative and has a different model structure, it performs significantly worse in terms of prediction as reflected by its higher RMSE values compared to the MDCEV models; therefore, the final eMDC model will only be compared with a restricted eMDC in which all δ parameters are fixed to 0. Also, apart from the two MDCEVs in Table 3, the performance of a mixed MDCEV with only alternative-specific random errors is presented for illustration purposes. The metric we used for evaluation is the Root Mean Square Error (RMSE) of the aggregate prediction in the whole sample.

First, the three MDCEV models are compared. It is noted that incorporating only independent random error components can lead to worse prediction performance in terms of continuous consumption. After incorporating correlations, the prediction is much improved and closer to the real values. Other research, for instance, Calastri et al. (2020), also made similar observations.

Apart from the percentage of respondents who choose shared EV and shared e-bike, how many people choose both eHUBS modes simultaneously was also checked. According to the correlation criterion of complementarity in Manzini et al. (2019), if $P(A)*P(B) < P(AB)$, then A and B can be considered as complementary,[2] in which P(A) and P(B) are the percentages of respondents choosing A and B respectively, while P(AB) is the percentage of respondents who chooses both A and B (independently of the number of allocated days). Although this criterion cannot be directly applied to statistics for our full sample because it consists of choices between alternatives with different attribute combinations, it is still possible to observe how well each model can recover P(AB) as an indicator of its capability in capturing complementarity. Although MDCEV model can reproduce the pattern of time allocation and discrete choice shares considerably well, it underpredicts the share of transport users who would choose both eHUBS modes. This underprediction is even more severe in the mixed MDCEV without correlation. Although mixed MDCEV model with correlation still slightly underpredicts the share who choose both eHUBS modes, the result is already the closest to actual values among all three MDCEV models in terms of the share choosing both shared modes, demonstrating its capability in capturing the complementarity between the shared modes.

The prediction of the first two eMDC models (without and with δ parameters) are very similar in terms of time allocation and discrete choice proportions, while the significant difference lies in the share of transport users who choose both eHUBS modes. Even though both the share of people choosing shared EV and shared e-bike are overpredicted, the eMDC model without complementarity and substitution effects still underpredicts the share choosing both eHUBS modes. Due to the strong complementarity effect in the eMDC model with interactions, the share that chooses both eHUBS modes is predicted to be much higher than in the eMDC model without interactions, although it is an overprediction compared to the actual value. Finally, the mixed eMDC incorporating alternative correlation via error component performs significantly better than the first two eMDCs in terms of all prediction performance indicators: the prediction for both continuous consumption and share of people choosing an alternative is closer to the actual value, its overprediction of the percentage choosing both eHUBS modes is also much less than the eMDC model without alternative correlation, implying that the shared error component and the δ parameters (for comeplementarity and substitution) are each capturing a unique behavioral mechanism.

Based on the above estimation and analysis, it can be concluded that the complementarity between the two eHUBS modes does exist and there is added value in providing multiple shared modes in mobility hubs.

5.2. Flexibility between the eHUBS modes

5.2.1. Pattern of choice adaptation

As it was mentioned in the survey design section, the respondents were asked to indicate how they would change their choices if shared EV or e-bike become unavailable. By contrasting their choices under different mode availability conditions (Q1, Q2.1, and Q2.2) and analysing their choice adaptation strategies, it is necessary to derive insights regarding transport users' flexibility between the two eHUBS modes.

Table 6 presents the choice adaptation pattern for each current choice response. For example, the first row indicates that for the 168 choice observations in which only shared EV was chosen to conduct all their trips, 24.4 % of those would use only the shared e-bike to replace all trips when shared EV becomes unavailable, 62.5 % would completely switch back to their private car and the remaining 13.1 % would use both e-bike and private car to replace shared EV. These choices were made under different choice tasks with varied attribute combinations, so the table is only supposed to provide an indication. Although the adapted choices were elicited for all tasks,

[2] As discussed in section 2, this condition is necessary but not sufficient in multiple discrete continuous choices with fixed budget.

only those who are forced to adapt are presented in Table 6. For example, people who choose the private car to conduct all trips in Q1 are not included because they do not have to adapt when the availability of eHUBS modes changes.

From Table 6 the following observations can be drawn: Firstly, those who choose to replace all trips by using a private car can be considered to be completely inflexible since they do not use the remaining shared service in the hub at all; therefore the percentage adopting this strategy can be seen as an indicator for different groups' flexibility between the use of two shared modes. The ranking of flexibility between eHUBS modes from the most to least flexible is: those who chose shared EV + e-bike, those who chose all three modes, those who chose only shared EV or e-bike, those e who chose car and one of the eHUBS mode. It is plausible that those who initially only chose one of the eHUBS modes are more inflexible: they probably did not choose both modes because the unchosen shared mode may not meet their needs; Secondly, those who choose to replace the unavailable mode only with the other eHUBS mode can be considered as being completely flexible. Among those who chose both eHUBS modes in Q1, a rather high percentage (40 % – 55 %) adopt this adaptation strategy; this is intuitive since they already chose the other eHUBS mode when all modes were available, which implies that both modes are considered suitable. Even among those who initially chose only one eHUBS mode, there is also a significant minority who are completely flexible: for example, 24.4 % of people who initially chose shared EV to conduct all their trips will switch completely towards shared e-bike when EV becomes unavailable; Thirdly, in general, EV seems to be able to replace e-bike to a slightly higher extent. For example, among those who only chose shared EVs to conduct all trips, 24.4 % are willing to completely switch toward shared e-bikes as a replacement; while among those who only chose shared e-bikes, the percentage of completely flexible people increases to 34.2 %.

5.2.2. Statistical models

Using pooled response data for Q1, Q2.1 and Q2.2, three models, which are respectively MDCEV, mixed MDCEV, and emergent value model were estimated. Since our focus in this section is to predict people's behaviour adaptation when the availability of shared mode changes, we will not apply eMDC in this section as we see from section 5.1 that eMDC does not perform better in terms of general prediction performance. The estimation results can be found in Table 7. Of all three models, the mixed MDCEV model has the highest model fit with the highest log likelihood, but this may mostly be due to.

its incorporation of unobserved random taste heterogeneity and it does not necessarily correspond to better predictive performance (Krueger et al., 2021). The impact of socio-demographics on the ASC was examined while only those that are statistically significant were retained in the final model: people below 35 years old show a higher preference for both shared EVs and e-bikes, while those who are male or with children have a higher preference for shared e-bike. The emergent value model has a higher log-likelihood than the base MDCEV model. The emergent values of both shared EV and e-bike are positive and statistically significant: this indicates that when the other shared mode is unavailable, the usage of both shared EV and e-bike would increase so much as if their utilities increase. We also investigated the impact of socio-demographics on the ASC and the emergent value of both shared modes. The results are similar to the case of the mixed MDCEV model: the only difference is that only those with higher education are found to prefer shared EV. Not much heterogeneity is observed in emergent values: only those with higher education are found to have a lower emergent value for shared EV, implying that they would use shared EV as a replacement to a lesser extent when shared e-bike is unavailable.

Table 8 presents the results of the base forecast for all models. The column "original data" lists the actual values of the original sample. The root mean squared error (RMSE) of the aggregate predictions is used as the indicator of forecast error (Palma et al., 2021; Palma and Hess, 2022). It is calculated separately for each choice context (Q1, Q2.1 and Q2.2). We first check whether the model estimated only using responses for Q1 can generate accurate prediction when one of the eHUBS modes becomes unavailable. Column 2 shows that the MDCEV model estimated based on Q1 data severely underpredicts (around 20 % less) the number of trips allocated to eHUBS under Q2 contexts: this indicates that the flexibility between the two shared modes is stronger than MDCEV model implies. Since a possible reason for this phenomenon is common preference heterogeneity, mixed MDCEV model which accommodates correlations between alternatives may be able to generate the choice adaptation patterns under Q2 better: as per column 3 its prediction in Q2 contexts is indeed much better than MDCEV model (for example, its RMSE for the Q2.1 context is only 657.94, much smaller than the RMSE of MDCEV which is 1390.24), although the predicted use of shared mobility is still lower than the actual value.

The next step is to explore whether models estimated with all data (Q1 and Q2) perform better: column 4 shows that the prediction

Table 5
Prediction of models based on the collected sample.

	Original data	MDCEV	Mixed MDCEV without correlation	Mixed MDCEV with correlation	eMDC with all δ fixed to 0	eMDC	Mixed eMDC
Continuous consumption (When total number of trips is 10)							
Car	7.76	7.69	7.51	7.65	7.09	7.09	7.37
Shared EV	1.10	1.13	1.17	1.10	1.42	1.43	1.29
Shared e-bike	1.15	1.18	1.32	1.25	1.47	1.45	1.30
RMSE		169.46	646.22	308.58	1660.12	1655.2	949.7
Share of people choosing an alternative							
Car	87.6 %	86.3 %	85.3 %	86.0 %	86.1 %	84.2 %	85.5 %
Shared EV	20.2 %	20.5 %	20.4 %	20.1 %	25.2 %	26.1 %	23.4 %
Shared e-bike	20.5 %	20.6 %	21.6 %	21.2 %	25.1 %	26.3 %	23.3 %
Both eHUBS modes	6.8 %	4.1 %	2.9 %	5.7 %	4.8 %	11.2 %	8.7 %

Table 6
Choice adaptation when an eHUBS mode becomes unavailable (Q2).

Choice when all three modes are available (Q1)	Number of choice occurrences	Replace only with another eHUBS mode	Replace only with private car	Replace with both modes
Shared EV only	168 (4.7 %)	24.4 %	62.5 %	13.1 %
Shared EV + car	307 (8.6 %)	14.7 %	72.6 %	12.7 %
Shared e-bike	199 (5.6 %)	34.2 %	52.3 %	13.6 %
Shared e-bike + car	286 (8.1 %)	11.2 %	75.2 %	13.6 %
Shared EV + e-bike	74 (2.1 %)			
Only EV available		55.4 %	27.0 %	17.6 %
Only e-bike available		43.2 %	32.4 %	24.3 %
All three modes	168 (4.7 %)			
Only EV available		39.3 %	27.4 %	33.3 %
Only e-bike available		42.3 %	35.1 %	22.6 %

Table 7
Estimation results of models for pooled data.

	MDCEV		Mixed MDCEV		Emergent value	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Car						
ASC	0.000		0.000		0.000	
Access time	*−0.018*	*−1.882*	**−0.038**	**−2.749**	*−0.018*	*−1.896*
Travel time	−0.013	−1.182	−0.013	−0.836	−0.014	−1.229
Travel cost	*−0.091*	*−1.799*	**−0.249**	**−3.768**	*−0.090*	*−1.792*
Parking time	−0.010	−1.159	**−0.027**	**−2.385**	−0.010	−1.145
Parking cost	**−0.146**	**−10.020**	**−0.294**	**−13.161**	**−0.144**	**−10.001**
Congestion time * probability	−0.505	−1.258	−0.798	−1.373	−0.500	−1.249
Shared EV						
ASC**	**−0.861**	**−4.660**	**−2.460**	**−8.727**	**−1.141**	**−5.557**
Higher education					**0.260**	**2.002**
Young			*0.370*	*1.875*		
Shopping trip	−0.090	−1.385	**−0.267**	**−2.769**	−0.088	−1.349
Access time	**−0.039**	**−5.971**	**−0.067**	**−7.743**	**−0.039**	**−5.962**
Travel time	**−0.055**	**−4.738**	**−0.102**	**−6.233**	**−0.056**	**−4.768**
Unit travel cost per minute	**−2.463**	**−5.470**	**−3.240**	**−5.362**	**−2.458**	**−5.436**
Congestion time * probability	−0.414	−0.989	−0.525	−0.864	−0.417	−0.978
Shared e-bike						
ASC**	**−1.993**	**−9.142**	**−4.067**	**−11.395**	**−2.104**	**−9.697**
Male	**0.298**	**2.377**	**0.591**	**2.477**	**0.299**	**2.369**
Young	**0.251**	**2.044**	**0.592**	**2.277**	**0.255**	**2.055**
Have children	**0.360**	**2.941**	**0.652**	**3.013**	**0.361**	**2.929**
Shopping trip	**−0.484**	**−7.064**	**−1.033**	**−9.153**	**−0.485**	**−7.073**
Access time	**−0.027**	**−3.927**	**−0.051**	**−5.343**	**−0.027**	**−3.868**
Travel time	**−0.020**	**−2.194**	**−0.054**	**−4.181**	**−0.020**	**−2.172**
Travel cost	**−0.200**	**−2.092**	**−0.462**	**−3.355**	**−0.200**	**−2.082**
γ: Car	**1.272**	**7.087**	**0.450**	**8.776**	**1.335**	**6.783**
γ: Shared EV	**0.814**	**12.568**	**0.449**	**10.889**	**0.793**	**12.661**
γ: Shared e-bike	**0.822**	**11.457**	**0.362**	**10.483**	**0.804**	**11.590**
σ: Shared EV			**0.739**	**6.127**		
σ: Shared e-bike			**2.270**	**20.021**		
σ: eHUBS modes			**2.867**	**22.458**		
Emergent value EV					**0.425**	**5.341**
Higher education					**−0.285**	**−3.230**
Emergent value E-bike					**0.208**	**6.188**
Number of individuals		819		819		819
Number of observations		10,653		10,653		10,653
LL		−9260.8		−6781.5		−9242.58

** Estimate of mean in mixed MDCEV.
Bold: statistically significant at 0.05 level. *Italic*: statistically significant at 0.1 level.

of the MDCEV model estimated using all data has smaller RMSE for Q2 choices, but this is at cost of overpredicting the share for eHUBS modes in Q1. The result of mixed MDCEV model in column 5 is similar: it performs better than MDCEV model and even overpredicts the share of eHUBS modes in Q2, but the percentage increase from the share under Q1 is still less than the actual value. Moreover, we can see that it even performs significantly worse than the mixed MDCEV model estimated with only data from Q1 (column 3) both for Q1 and Q2.2; this implies that in our case the additional data from Q2.1 and Q2.2 do not lead to a higher overall performance of mixed

Table 8
Base forecast results of different models.

	Original data	Q1 MDCEV	Q1 Mixed MDCEV	Pooled MDCEV	Pooled Mixed MDCEV	Emergent value
All three modes available (Q1)						
Continuous consumption						
Car	7.76	7.69	7.65	7.39	7.45	7.62
Shared EV	1.10	1.13	1.10	1.31	1.20	1.18
Shared e-bike	1.15	1.18	1.25	1.30	1.35	1.20
RMSE		169.46	308.58	941.33	788.31	350.06
Share of discrete choice						
Car	87.6 %	86.3 %	86.0 %	84.5 %	83.6 %	86.1 %
Shared EV	20.2 %	20.5 %	20.1 %	22.2 %	20.4 %	20.2 %
Shared e-bike	20.5 %	20.6 %	21.2 %	22.0 %	21.8 %	20.4 %
Only Shared EV available (Q2.1)						
Continuous consumption						
Car	8.31	8.70	8.49	8.46	8.29	8.34
Shared EV	1.69	1.30	1.51	1.54	1.71	1.66
RMSE		1390.24	657.94	550.35	78.55	111.55
Share of discrete choice						
Car	90.9 %	93.0 %	92.1 %	91.7 %	90.1 %	90.8 %
Shared EV	26.7 %	23.0 %	24.8 %	25.5 %	26.1 %	27.3 %
Only Shared e-bike available (Q2.2)						
Continuous consumption						
Car	8.37	8.65	8.43	8.47	8.26	8.36
Shared e-bike	1.63	1.35	1.57	1.53	1.74	1.64
RMSE		991.98	186.22	337.41	406.94	33.31
Share of discrete choice						
Car	91.2 %	92.6 %	91.0 %	91.7 %	89.2 %	90.9 %
Shared e-bike	26.6 %	23.0 %	24.8 %	25.4 %	25.9 %	26.9 %

MDCEV. Finally, it is observed that the emergent value model has the smallest RMSE in all three choice contexts and overall has the best ability in recovering the statistics of the estimation sample.

The results of the cross-validation can be found in Table 9. Although mixed MDCEV model has higher model fit, it does not outperform MDCEV in terms of its aggregate prediction of both continuous consumption and discrete choices. On the other hand, the emergent value model has the smallest RMSE for both the aggregate prediction of continuous consumption and discrete choices. There is little difference between all models in terms of the RMSE per alternative.

To summarize, the emergent value model has the best overall prediction performance. Given these results, it is possible to conclude that common preference heterogeneity between the two shared modes is not the (only) reason underlying the strong flexibility between eHUBS modes and cannot represent the true data-generating process. The real behavioural mechanism which can generate strong flexibility between shared modes will still need to be explored; otherwise, the prediction results will be biased when the model estimated under a certain choice context is applied in different choice contexts (alternative availability).

6. Conclusions, policy implications and future work

This paper investigates transport users' mode choice behaviour when electric mobility hubs become available. As the integration of different transport modes provides easier access to a wide range of transport services, many transport users are expected to use multiple transport modes to conduct their trips. Therefore, multimodal behaviour both in our measurement and modelling of the mode choice behaviour was explicitly accommodated. Instead of asking the respondents to indicate their most preferred mode, the stated choice experiment that was designed for the study asks them to allocate the number of trips between different modes which allows multiple modes to be chosen. Several models under the Multiple Discrete Continuous framework were then applied to model the choice data.

We investigate whether there is complementarity or substitution between the multiple shared modes available in the eHUBS. We use two approaches to accommodate complementarity and substitution in the models: first, we estimate a mixed MDCEV model which can capture complementarity via correlations between alternatives. Although we find a positive correlation between the two eHUBS alternatives shared electric vehicle and shared e-bike, it does not allow us to conclude whether this correlation is due to common preference heterogeneity or complementarity. We then estimate an eMDC model which explicitly includes multiplicative terms representing the interaction between different alternatives and allows the identification of complementarity and substitution. The result of the eMDC model shows that there exists complementarity between shared EV and shared e-bike in eHUBS, providing evidence for the added value of offering both services at the same physical location.

We also study how travellers adapt when one of the shared modes becomes unavailable. Those who chose both shared modes initially are the most flexible to use the remaining shared mode for replacement, while those who chose private car and only one of the shared modes are the least flexible. However, even this least flexible group is willing to use the remaining shared mode as (part of the) replacement in around 25 % of the cases. it is found that the standard MDCEV model estimated with choice data when all modes are available would underpredict the use of shared mobility service in eHUBS when one of the shared modes is unavailable, implying that

Table 9
Cross-validation results of different models.

	MDCEV	Mixed MDCEV	Emergent value
Continuous consumption (When total number of trips is 10)			
Aggregate RMSE			
Total	227	238	192
All three modes available (Q1)	103	94	72
Only Shared EV available (Q2.1)	68	66	57
Only Shared e-bike available (Q2.2)	56	78	63
RMSE per alternative			
All three modes available (Q1)			
• Car	3.58	3.53	3.56
• Shared EV	2.55	2.53	2.53
• Shared e-bike	2.70	2.68	2.69
Only Shared EV available (Q2.1)	3.15	3.14	3.15
Only Shared e-bike available (Q2.2)	3.16	3.15	3.16
Discrete choices			
Aggregate RMSE			
Total	23.4	25.6	21.2
All three modes available (Q1)	11.2	11.4	9.5
Only Shared EV available (Q2.1)	4.7	4.9	4.0
Only Shared e-bike available (Q2.2)	7.4	9.3	7.7

MDCEV model assumes less flexibility between shared modes than in reality. It was then tested whether common preference heterogeneity is the underlying cause for the choice adaptation pattern by a mixed MDCEV model with correlations between alternatives; the results show that it cannot fully represent the real data generating process and the genuine behavioural mechanism is still an open question.

Our study and findings have several policy implications. First, the fact that we find a significant group of travellers prefer to use a combination of multiple modes demonstrates the relevance of multimodal responses in stated choice experiments on passenger mode choices; the data collection protocol and modelling framework in this paper can also be applied in future studies on mode choice and multimodal behaviour. Second, many local governments are planning to deploy mobility hubs as one of the means towards sustainable mobility but their actual impacts on mobility behaviour is inconclusive; by showing that there is complementarity between shared EV and e-bike offered in mobility hubs, our study provides empirical evidence regarding the added value of mobility hubs in promoting shared mobility and reducing the use of private cars. Third, when we study how travellers adapt if one of the shared modes becomes unavailable, we find that MDCEV and mixed MDCEV models cannot fully account for people's flexibility between shared modes, we also show that mixed MDCEV models perform worse than the ad-hoc emergent value models in terms of out-of-sample prediction. It raises precaution for the model transferability of existing MDC models since its prediction of demand can be biased under different choice contexts (alternative availability). This can be remedied by collecting choice/demand data under varied mode availability conditions or develop better behavioural models with mechanisms that can better accommodate people's flexibility between shared modes.

A drawback of this study is that we assume the respondents only have a single current mode, while they may actually be using multiple modes. Since our study only included private car drivers, this may potentially lead to an overestimation of the impact of eHUBS modes on replacing private car trips, because the "private car drivers" may be multimodal and are actually already using other modes such as biking and public transit for a few trips. Similar studies in the future should better capture respondents' current mode usage to achieve more accurate results. Another limitation of the work is that we fix the total number of trips for all respondents, implicitly assuming that the proportion allocated to each mode remains fixed regardless of the total number of trips. This assumption may not necessarily be true, for example, if people can work from home for more days and conduct fewer commuting trips per week, this may affect their selection of modes. Moreover, the provision of innovative modes such as eHUBS may also lead to induced demand, which cannot be investigated under our current study design. Future studies may adopt a response format without an identical fixed budget (such as the number of trips conducted during a certain time period) and apply models such as eMDC with an implicit budget for the analysis.

There are several avenues for future research. First, more modes (both existing and innovative ones) can be included in the choice experiment to achieve a more complete representation of people's choice behaviour between all available modes. Under the MDC framework, one may investigate how driving a private car may be replaced by a combination of public transit and shared mobility modes. It also allows the exploration of relations between other shared modes and the relations between shared modes and other existing modes (e.g. public transit) using the MDC framework. It would be valuable to investigate other trip contexts as well, such as longer trips which can be intermodal in which eHUBS modes serve as a first/last mile mode. Second, future studies can investigate how complementarity, substitution, and flexibility between modes vary in different trip contexts, geographical locations, and time periods. For example, for commuting trips with more time pressure, people may be more inclined to use a single mode and the level of complementarity would be relatively lower. The terrain, culture, and social norms regarding transport modes in different countries and regions may also influence the complementarity and flexibility between modes. Third, explore other behavioural mechanisms and advanced modelling approaches which can better explain the flexibility between modes.

CRediT authorship contribution statement

Fanchao Liao: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dilum Dissanayake:** Writing – review & editing, Investigation. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Project administration, Investigation, Conceptualization.

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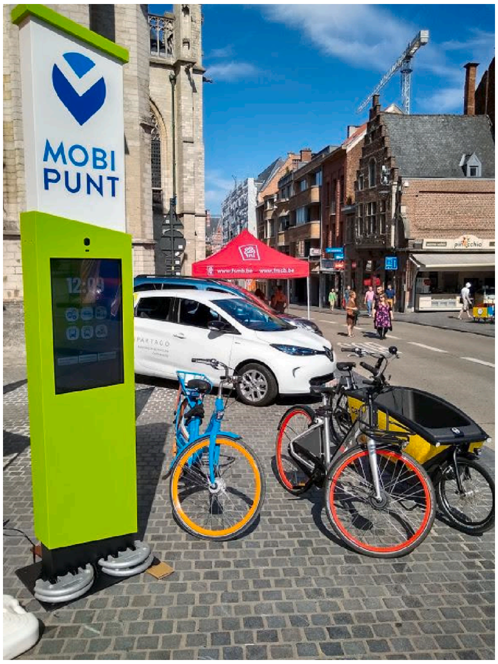
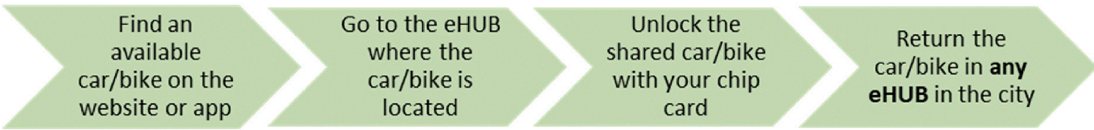
Appendix I. . Introduction of eHUBS in the survey

eHUBS are on-street locations in residential neighbourhoods, or at bus or train stations, that offer citizens access to a range of publicly shared vehicles including electric (cargo)bikes, e-scooters, or electric cars (see the following figure for an example).



Assume there are eHUBs in your city which are mobility hubs providing both shared electric vehicle and shared e-bikes (including e-cargo bikes). The following picture illustrates the process of using and returning an eHUB car/bike:



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