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A case of shared electric mobility hubs (eHUBS) in Amsterdam and Manchester

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ABSTRACT

Electric mobility hubs (eHUBS) represent an innovative approach to providing diverse shared electric transportation options, aimed at curbing private car use, and mitigating associated environmental impacts. Assessing the impact of eHUBS on travel choices across different cities requires significant resource and time investment due to the need for localized data collection and model development. This paper proposes a potential solution to this challenge by investigating the transferability of mode choice models originally developed for eHUBS in Amsterdam to predict behaviour towards eHUBS in Manchester.

Multinomial Logit (MNL) and mixed logit models were transferred using four different procedures, and their effectiveness was evaluated using three assessment measures. The findings indicate that a scaled mixed logit model with an updated Alternative Specific Constant (ASC) outperforms other models in terms of its transfer effectiveness, both for disaggregate and aggregate assessment measures. The interplay between transfer procedures and assessment measures also was examined, with results indicating enhancements in disaggregate transferability measures with the 'scaling' transfer procedure, while 'updating the Alternative Specific Constants (ASCs)' improved predictions of aggregate mode shares. Following the analysis, the paper presents an in-depth discussion to provide a nuanced understanding of transferability and thus offers valuable insights for researchers planning future studies and practical considerations for policymakers.

1. Introduction

Urban transportation planning is undergoing a significant transformation due to the rapid growth of new mobility services grounded in shared economy principles and vehicle electrification (Jenn et al., 2018; Pan et al., 2021). The proliferation of novel modes and services has significantly expanded the mobility options available to individuals by offering a spectrum of services tailored to meet diverse travel needs. The disruptive changes occurring in the urban mobility ecosystem carry the potential to alleviate longstanding challenges resulting from the inefficient transportation systems such as vehicle emissions, traffic congestion, equity disparities, connectivity limitations, and accessibility barriers (Joshi et al., 2021; Peer et al., 2024). The realization of the anticipated transformative impacts of shared electric mobility systems hinges upon the extent to which these can align with user preferences and induce behavioural shifts among commuters. As a result, it becomes imperative to comprehensively understand the factors that influence user preferences and, consequently, their choices of travel modes and services.

Analysing the shifts in travel behaviour resulting from the introduction of new mobility services necessitates the development of discrete choice models that elucidate the underlying factors driving such behaviour (Kang et al., 2024). The data essential for estimating these models are typically gathered from survey participants through a range of methods, including online questionnaires or interviews either computer-aided, face-to-face or by telephone. However, the data

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collection process presents significant challenges, requiring substantial efforts and resources to identify potential respondents, reach the target sample size, and hire interviewers (Behrens et al., 2006). Even when data is available from secondary sources, it is often not open source, requiring financial investment to access. Moreover, the complexity is further heightened when behavioural models need to be estimated using data from multiple geographical locations, thereby amplifying both time and monetary costs. One approach to address this challenge is to explore model transferability, which aims to minimize the necessity of collecting data from multiple locations. This strategy can lead to substantial savings in both time and effort required for data collection.

Transferability, as defined by (Koppelman and Wilmot, 1982), refers to the utility of a model developed in one context in explaining behaviour in another context. In essence, if a model originally developed to understand mode choice behaviour in one setting can effectively explain behaviour in a new, unobserved context, this could reduce or eliminate the need for new data collection efforts. The literature on transferability can be broadly categorized into two main domains: spatial, which assesses transferability between different geographical locations (Pani et al., 2021), and temporal, which examines transferability across different time periods (Fox et al., 2014). Several studies have explored the transferability of models in a range of contexts. For instance, (Dissanayake et al., 2012) investigated the transferability of a mode choice model across four different metropolitan areas in Asia using existing databases. (Lefebvre-Ropars et al., 2017) evaluated the transferability of a pedestrian index of the environment originally developed for Portland, Oregon, to Montreal, Canada. Similar to the spatial transfer, the application of transfers across different times was studied by (Cabrera Delgado and Bonnel, 2016), where the trip distribution model developed for Lyon in France was tested on transferability across three decades.

Although the concept of transferability is not new having been introduced several decades ago and already found application in various studies, further advancements in addressing research gaps within this topic have been sparse. Specifically, we have identified several research gaps and inquiries, the resolution of which could enrich the existing body of literature on transferability. Firstly, transferability in the context of emerging modes of transportation has not been studied to the best of our knowledge. Secondly, the differences in assessment measures of model transfer depending on transfer procedures remains largely unexplored. The third gap pertains to the performance of different types of model structures in terms of transferability when applied to the same context. Finally, it is crucial to explore the policy and research considerations that should be accounted for in transferability analysis. This paper addresses the aforementioned gaps in the following manner:

- by examining the transferability of mode choice models within the context of emerging mobility services 'eHUBS,' which remain relatively new and unexplored in the literature.
- by understanding the relationship between different transfer procedures and assessment measures.
- by conducting transferability assessments for two distinct model types, previous studies have examined only one, and thereby shedding light on the influence of model specification on transferability outcomes.
- by presenting an in-depth discussion of the results specifically relating to the nuances in transferability analysis and thus offering valuable insights for planning future studies.

The paper is structured into six sections, with this introduction being the first. The second section establishes context by providing details about the eHUBS in both cities, outlines the data collection process, and presents descriptive statistics on the socio-demographic profiles. Following this, the third section presents the mode choice models developed for both cities, offering insights into the factors influencing mode choice behaviour. Section four delves into the theory of transferability and introduces a range of measures for evaluating the transferability. Moving on to section five, we discuss the results of the transferability analysis and finally, in the sixth section, we provide a discussion of the results and outline potential future research directions.

2. Context of the study

This section describes the case studies carried out in Amsterdam and Manchester, the data collection and the descriptive statistics of the data collected.

2.1. eHUBS in Amsterdam and Manchester

eHUBS provide at least two of a range of shared electric mobility options to users, aiming to reduce private vehicle usage. These eHUBS are undergoing pilot programs in numerous cities across Europe and aim to encourage sustainable mobility behaviours. Two of these cities, Amsterdam in the Netherlands, and Manchester in the United Kingdom, serve as the primary case study locations in our paper. Amsterdam, the largest city in the Netherlands, has a population close to a million (Savills World Research, 2018). With a particular emphasis on facilitating first-mile travel and reducing the need for parking, the City of Amsterdam has established 17 eHUBS across strategic areas within the city. Amsterdam is renowned for its commitment to promoting cycling, backed by state-of-the-art infrastructure facilities for cyclists (Nello-Deakin and Nikolaeva, 2021). Now, with the advent of electric mobility, Amsterdam seeks to integrate new mobility forms such as eHUBS with its existing infrastructure. On the other hand, Manchester, known for its industrial heritage, has set ambitious decarbonization goals to achieve by 2038, with the transition to electric mobility forming a pivotal component of the city's decarbonization strategy (Transport for Greater Manchester, 2021). Transport for Greater Manchester (TfGM) inaugurated its first eHUB in October 2021 and has plans to introduce additional eHUBS as funding is made available. The below Fig. 1 presents one of the eHUBS in Amsterdam.

The eHUBS initiative offered shared electric vehicles in six pilot cities across five different countries and subsequently replicated the concept in other European cities (Bösehans et al., 2021). A successful transferability of a model developed for one eHUBS city in explaining choices related to eHUBS in another city could potentially pave the way to its wider application in all other cities contemplating eHUBS implementation, thus saving a significant amount of time and resources involved in data collection and analysis. The process of developing a mode choice model, encompassing data collection, survey design, and analysis, was undertaken previously in eHUBS project by (Liao et al., 2024) and does not constitute the main focus of the current paper. Instead, the current paper exclusively focuses on the transferability of previously developed models, and thus provides limited discussion on the model estimation and behavioural interpretation. However, to set the context for the subsequent transferability analysis, the focus of this paper, a concise explanation of the model development is provided below.

2.2. Data collection

Data collection in both cities was conducted through an online survey containing questions related to respondents' mobility profiles, information on their current trip, socio-demographic characteristics, and stated preference choice questions to investigate individuals' mode choices for a hypothetical scenario where shared electric mobility services become available for their work-related commuting trips. Before administering the survey, respondents were presented with specific assumptions regarding the hypothetical scenario. These included clarifying that eHUBS represent a one-way station-based system, wherein vehicles can be hired from an eHUB station and returned to any other station within the same city. Moreover, it was explicitly communicated that vehicles would always be available at the eHUBS station. A market

Fig. 1. EHUBS in Amsterdam.

research panel company was engaged to distribute the online questionnaire and responses captured in a server for subsequent analysis. The data collection was carried out in March 2021. The survey targeted individuals above the age of 18 holding a driver's license, residing in either Amsterdam or Manchester. Each respondent was asked to answer six choice questions out of 27 alternative tasks which were orthogonally designed by varying different attributes consisting of access time, parking search time, travel time, changes in congestion, and travel cost. An efficient design was not considered because any good estimates for the coefficients of eHUBS attributes were not available at the time of study and D-efficient design is not robust when priors are far from the real value (Walker et al., 2018). Therefore, the respondents choose between current mode that they use (Status Quo - SQ) or eHUBS as an alternative, i.e., either Shared Electric Vehicle (car) - SEV or Shared Electric Bike -SEB in each of the six choice tasks that were randomly shown. All choice tasks in the design appeared roughly an equal number of times, thus facilitating the random procedure adopted in the survey. The attribute values of the current mode alternative were fixed as the real values provided by the respondent, whereas the attributes and their levels used for designing the experiment are given in Table 1. An example of a choice experiment is given in Fig. 2.

2.3. Descriptive comparison

Following a data cleaning process, a complete and valid dataset comprising 358 individuals (2148 data points) from Amsterdam and 337 individuals (2022 data points) from Manchester was used for analysis. Table 2 below presents a descriptive comparison of the socio-demographic data from the collected samples in both cities and the corresponding population proportions in each of these cities compiled from various sources. The descriptive statistics provide insights into the similarities and differences between the two cities.

The analysis of the sample reveals that both cities exhibit a similar socio-economic profile concerning income level, gender distribution, education, and car ownership. Notably, despite Amsterdam's reputation as the bicycle capital of the world, over 95% of households in both Amsterdam and Manchester possess at least one car. Differences between the two cities emerge primarily in terms of employment status, age demographics, and the number of children within households. Fig. 3 illustrates the comparison of current mode shares in both cities, highlighting significant differences. In Manchester, approximately one-third of all work trips are undertaken using private cars, with public transport ranking as the second most preferred mode. In contrast, Amsterdam exhibits a distinct pattern, with only 38% of trips conducted via private cars, an equal share for bicycles.

3. Mode choice models

Data from both Amsterdam and Manchester were collected concurrently, with the estimation of models using Amsterdam data taking place first. Subsequently, the Manchester models were separately estimated, employing the same model specifications as the Amsterdam models. The sole distinction between these two sets of models lies in the omission of variables related to 'bikes' as the current mode in case of Manchester. This exclusion is due to the relatively small sample size of bike users, making it challenging to reliably estimate model parameters associated with bikes. It is important to note that this omission does not impact transferability, as all parameters present in the Manchester model are also present in the Amsterdam model, making transferability of complete model feasible.

Both Multinomial Logit (MNL) and Mixed Logit models were estimated for both cities using the Biogeme software package (Bierlaire, 2023) and the results are shown in Table 3. The probability of choosing the mode between eHUB and current mode depends on the mode attributes (travel time, cost, access time, etc.) and socio-demographic variables of respondent (gender, age, income, etc.). The mixed logit

Table 1
Attributes and their levels.

Attributes	eHUBS	
	SEV	SEB
Travel time (minutes)	If the current mode is private car, same as car. Otherwise:Reference: *80%,100%,120% Reference is calculated based on distance assuming 30 km/h	Reference: * 80%,100%,120%Reference is calculated based on distance assuming 20 km/h
Access - egress time (minutes)	2 10 18	2 10 18
Travel cost (€ or £ per minute)	0.15 0.25 0.35	0.5 (regardless of distance) 1.5 (regardless of distance) 2.5 (regardless of distance)
Congestion level (minutes)	If current mode is private car, same as car. Otherwise:Chance of delay: 0%, 20%, 40% Possible delay: 25%, 50%, 75% of travel time	

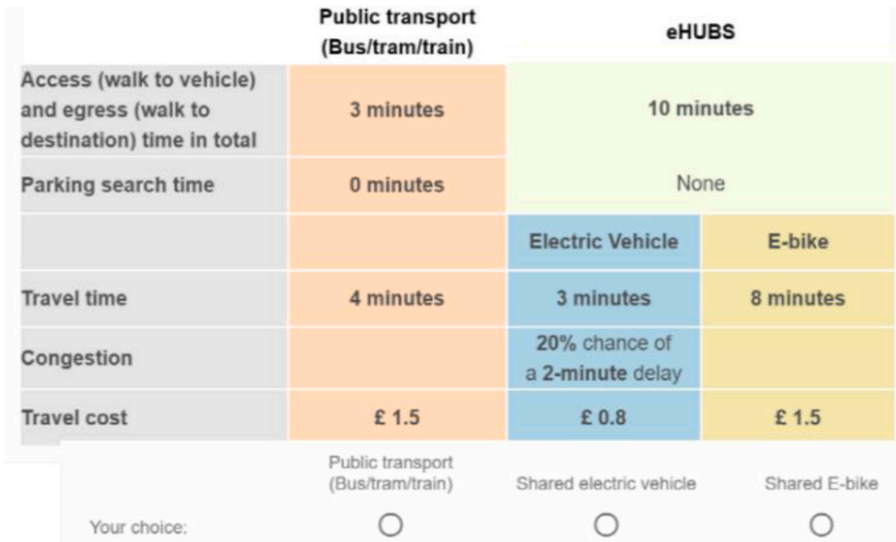

Fig. 2. Choice task example.

Table 2
Descriptive statistics.

Variable	Categories	Sample proportion (%)		Population in proportion (%)	
		Manchester	Amsterdam	Manchester	Amsterdam
Gender	Male	38	41	50.6	50.4
	Female	62	59	49.4	49.6
Age	18–24	12	11	26.9	12.0
	25–34	32	28	16.7	26.2
	35–44	31	26	10.4	17.4
	45 or older	25	36	46.0	44.5
Education	No higher education	40	36	61	52
	Higher education	60	64	39	48
Income[a]	Low ($\leq$ 40000)	50	49	–	–
	Middle (>40000 $\leq$ 80000)	37	38	–	–
	High (>80000)	10	9	–	–
	Missing values	3	5	–	–
Employment status	Employed	81	72	73	68.1
	Student	7	7	27	8.1
	Others	12	21		23.8
Car Ownership	0	4	5	39	60
	1	43	44	43	40
	more than 1	53	52	18	
No of children	0	50	60	70	76
	1	19	17	30	11.7
	more than 1	31	23		12.13

[a] Manchester's income levels are in GBPs and Amsterdam's income levels are in Euros.

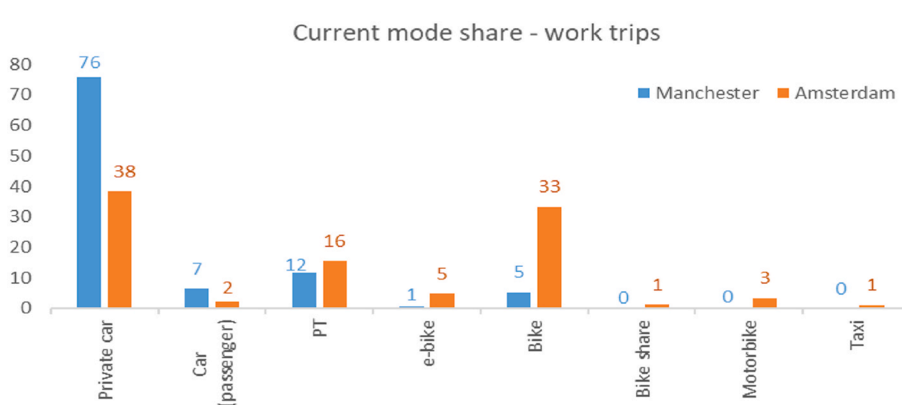

Fig. 3. Current mode shares.

Table 3
MNL and mixed logit models for Amsterdam and Manchester.

Parameter name	MNL model				Mixed logit model			
	Amsterdam		Manchester		Amsterdam		Manchester	
	Est	**p-val**	**Est**	**p-val**	**Est**	**p-val**	**Est**	**p-val**
ASC-Shared Electric Bikes								
Mean	−2.57	0.00	−1.64	0.00	−3.53	0	−3.61	0
Public transport users	0.78	0.16	1.11	0.02	1.44	0.16	2.81	0.05
Public transport users, 5 km or more	1.26	0.01	−0.35	0.42	1.42	0.14	−0.64	0.67
Standard deviation	–	–	–	–	−2.09	0.00	3.72	0.00
ASC-Shared Electric Vehicles								
Mean	−2.00	0.00	−2.39	0.00	−3.28	0.00	−5.99	0.00
Public transport users	−0.17	0.76	4.88	0.00	−0.63	0.63	9.34	0.00
Public transport users, 5 km or more	1.75	0.00	1.45	0.02	3.06	0.02	2.33	0.20
Standard deviation	–	–	–	–	−2.25	0	−3.62	0.00
Mode attributes- Shared Electric Bikes								
Access/Egress time	−0.06	0.00	−0.06	0.03	−0.07	0.00	−0.16	0.00
SEB: Car users' Access/Egress time	0.02	0.42	−0.08	0.00	0.04	0.15	−0.14	0.00
SEB: Travel cost	−0.34	0.00	−0.62	0.00	−0.47	0.00	−1.35	0.00
SEB: Travel time	−0.03	0.01	−0.06	0.00	−0.05	0.04	−0.15	0.00
Mode attributes-Shared Electric Vehicles								
Access/Egress time	−0.03	0.02	−0.08	0.00	−0.03	0.07	−0.15	0.00
PT users' congestion time	−0.13	0.22	−0.05	0.56	−0.24	0.09	−0.13	0.34
Car users' congestion time	0.02	0.61	−0.15	0.40	0.06	0.56	−0.54	0.53
Car users' travel cost	0.14	0.11	−0.26	0.00	0.11	0.35	−0.48	0.00
PT users' travel cost	−0.37	0.00	−0.22	0.00	−0.43	0.01	−0.59	0.00
Travel time	−0.09	0.00	0	0.97	−0.11	0.05	−0.1	0.25
PT users' travel	−0.04	0.37	−0.36	0.00	−0.07	0.43	−0.63	0.00
Mode attributes-Current mode								
Access/Egress time	−0.01	0.42	−0.03	0.00	−0.01	0.72	−0.07	0.06
Congestion time	0.02	0.53	−0.75	0.00	0.07	0.40	−1.65	0.01
Travel cost	−0.23	0.00	−0.09	0.00	−0.29	0.01	−0.21	0.00
Parking cost	−0.03	0.05	0.02	0.1	−0.07	0.08	0.04	0.23
Parking search time	−0.09	0.00	−0.21	0.00	−0.11	0.06	−0.45	0.00
Travel time	−0.01	0.44	−0.06	0.00	0.01	0.81	−0.17	0.00
Socio-demographic-SEV								
Higher education	0.13	0.47	−0.16	0.38	0.02	0.96	0.35	0.58
High income ($\geq$ 80000)	−1.3	0.00	0.28	0.35	−1.6	0.01	0.42	0.68
Low income ($\leq$ 40000)	−0.67	0.00	0.00	1.00	−0.65	0.13	0.2	0.76
Male	0.13	0.43	−0.26	0.17	0.36	0.37	−0.11	0.86
Old age ($\geq$ 60)	−0.18	0.59	−2.44	0.00	−0.99	0.2	−3.95	0.08
Young age ($\leq$ 35)	0.98	0.00	−0.43	0.02	1.53	0.00	−0.93	0.15
Socio-demographic-SEB								
Higher education	−0.06	0.74	0.26	0.13	−0.07	0.87	0.56	0.33
High income ($\geq$ 80000)	−0.91	0.00	0.12	0.68	−1.26	0.03	0.08	0.93
Low income ($\leq$ 40000)	−0.19	0.32	0.12	0.51	−0.34	0.4	−0.76	0.2.
Male	0.37	0.04	0.16	0.34	0.28	0.45	0.09	0.87
Old age ($\geq$ 60)	−3.06	0.00	−0.52	0.19	−3.47	0.01	−0.37	0.76
Young age ($\leq$ 35)	0.51	0.01	−0.13	0.44	0.79	0.04	−0.11	0.86

model assumes that the averages of unobserved factors (ASC) in utility follow a random distribution across the sample, characterized by a normal distribution. Additionally, the panel structure of the data in the mixed logit model addresses the correlation between multiple responses from the same individual. Some of the parameter values in both models are mode-specific and contingent on the respondents' current mode of travel (either car or Public Transport - PT). These mode-specific parameters are denoted with labels such as 'Car users Access/Egress,' indicating the influence of access time on the preference for shared mode among respondents currently using a car as their mode of travel.

Initially, it appears that the estimated parameter values for both cities are quite distinct. However, it would be inappropriate to compare them and draw conclusions about behavioural differences unless specific factors are considered. These factors will be covered in Section 4 dedicated to the transferability analysis. We would like to reiterate the point that the model interpretation is not covered in this paper since transferability of these models is the primary focus and interested readers are referred to (Liao et al., 2024) for more details on each parameter. However, for the convenience of our readers, we will summarize the key features of the estimated model for Amsterdam. The analysis found that most travel time and cost coefficients for different modes have a negative sign, indicating a general preference against increased travel time and costs. On average, current users of public transportation traveling more than 5 km are more likely to switch to eHUBS. The attributes of existing modes, such as parking search time and parking time, significantly influence the likelihood of switching to eHUBS modes. Socio-demographic factors also play a role: younger individuals are more likely to use eHUBS, while older individuals are less likely to adopt these modes.

4. Transfer procedures and assessment

4.1. Transfer procedures

This sub-section of the paper explains the mechanisms by which a model can be transferred, also referred to as '*transfer procedures*'. Different transfer procedures used in the paper are as follows:

a) *Naïve transferability'*: The most straightforward method for transferring a model is known as "naïve transfer." In naïve transfer, the base model parameters are directly applied to the application data without any alterations. It is worth noting that the majority of transferability studies consistently report subpar performance of *naïve transfer* in terms of its ability to explain behaviour in the application context (Koushik et al., 2022; Santoso and Tsunokawa, 2005). Nonetheless, naïve transfer serves a valuable purpose by providing a reference point for comparing the effectiveness of other transfer procedures.

b) *Scaling:* Transferability can be significantly enhanced by adjusting the transferred model parameters to accommodate the differences in variance in the application context. Within the 'scaling' transfer procedure, the model parameters—excluding the Alternative Specific Constants (ASCs)—are initially scaled to address differences in variance and are subsequently applied to the application data. The rationale behind scaling lies in the assumption that respondents in the base and application contexts assign different degrees of importance to variables within the mode choice equation (Galbraith and Hensher, 1982). Scaling has been extensively employed in studies which use data from multiple sources and in studies that combine RP and SP data (Batarce et al., 2015; Bergantino et al., 2020). The idea in these studies is similar to that in our paper, i.e., accounting for the difference in variance (amount of scatter) between two contexts. The scale can be estimated using data from the application context, and studies have indicated that the data required for estimating the scale represents only a small fraction of what is needed to estimate a complete model for the independent application context (Koppelman et al., 1985).

c) *Updating ASC:* Another transfer procedure known as 'Updating Alternative Specific Constant (ASC)' involves accounting for differences in the average unobserved factors between the base and application contexts. This procedure operates under the assumption that all model parameters can be directly transferred to the application context, with only the constants (ASC) requiring adjustment. The ASC values are adapted to align with the aggregate mode share observed in the application context. Multiple studies have documented improvements in transferability following the scaling of parameters and the updating of model constants (Hadayeghi et al., 2006; Nohekhan et al., 2022; Santoso and Tsunokawa, 2010).

4.2. Transferability assessment measures

The evaluation of transferability can be conducted through various measures, broadly classified into three categories; 1) statistical test for parameter equality, 2) disaggregate transferability (log-likelihood based), and 3) aggregate transferability. Within each of these categories, these measures can be further categorized into two types of measure: relative and absolute. Relative measures assess the transferability of a model concerning another model, while absolute measures do not reference another model. For a comprehensive overview of these measures, readers are referred to a matrix presented by (Sikder et al., 2014). Table 4 below provides explanations exclusively for the measures used in this paper.

$LL(\beta_j)$ is the log-likelihood (LL) value for the transferred model [i.e., when base (Amsterdam) model parameters are transferred to the application data (Manchester data)].

$LL(\beta_i)$ is the LL value for the application model (i.e., LL of the model estimated using application data, i.e., Manchester data).

$LL(MS)$ is the LL value for the market share model (also referred to as a constants-only model).

PS_k is the predicted mode share for mode k given by the transfer.

OS_k is the observed mode share for mode k in application data.

For the convenience of our readers, we will adopt the following nomenclature throughout the paper to refer to different models:

- Amsterdam (or base) model: The model estimated using Amsterdam (or base) data.
- Manchester (or application) model: The model estimated using Manchester data.
- Transferred model: Refers to the parameters from the Amsterdam (base) model that have been applied to the Manchester dataset (application data).

The *Transferability Test Statistics (TTS)* assesses the transferability under the hypothesis that the two sets of parameters are equal. It comprises a dichotomous statistical test that either accepts or rejects the null hypothesis positing the equality of model parameters (Atherton and Ben-Akiva, 1976). However, due to various factors such as model specification and behavioural differences, achieving perfect model transferability is typically not attainable. Therefore, it becomes imperative to consider a continuous scale of transferability (McArthur et al., 2011).

The *Transferability Index (TI)* serves as a continuous measure of disaggregate transferability, evaluating the goodness of fit by employing log-likelihood values. The TI value ranges from 0 to 1, with 1 indicating that the transferred model performs as effectively as an application model in terms of explaining individual-level choices.

The *Root Mean Square Error (RMSE)* values give an aggregate-level measure, assessing the predictive efficiency of the transferred model in reproducing observed mode shares within the data. A lower RMSE value signifies enhanced predictive accuracy of the model.

5. Results of spatial transferability of models

The MNL and mixed logit models developed for Amsterdam were transferred using four procedures: 1) Naïve transfer, 2) scaling, 3) updating ASC, and 4) simultaneous scaling and updating ASC. The effectiveness of the transfer is evaluated using three measures: a) TTS, b) TI, and c) RMSE. The following subsections will delve into the details of these methods and present the transferability results.

5.1. Naïve transferability

The first transfer procedure is '*Naïve transferability*', where the parameters of the Amsterdam model are transferred to Manchester data without any changes. The deterministic part of the utility equation contains alternative specific constants and parameters of the transferred model as shown below:

$$V^A_m = ASC_t + \beta_t * X^A_{im}$$

Table 4
Transferability measures.

Measure	Category	Formula	Description
Transferability Test statistics (TTS)	Statistical measure	$-2\left[LL\left(\beta_j\right) - LL(\beta_i)\right]$	χ^2 distributed, checks the equality of the transferred model parameters with the application model parameters.
Transferability Index (TI)	Disaggregate measure	$\dfrac{LL\left(\beta_j\right) - LL(MS)}{LL(\beta_i) - LL(MS)}$	Checks the goodness of fit of the transferred model
Root Mean Square Error (RMSE)	Aggregate measure	$\left(\dfrac{\sum_k PS_k * ((PS_k - OS_k)/OS_k)^2}{\sum_k PS_k}\right)^{1/2}$	Aggregate level prediction of mode shares compared with observed shares

V_m^A is the utility of mode m in application context 'A'
ASC_t is the alternative specific constant of the transferred model (represented by 't')
X_{im}^A is the vector of attributes of mode 'm' and characteristics of individual 'i'
β_t transferred model parameters.

The outcomes of the naive transferability assessment for both MNL and mixed logit models, as assessed by the TTS measure, are presented in Table 5, where the likelihood of transferred model is indicated as LL (Bj), whereas the likelihood of application context model is LL (Bi).

The null hypothesis, that the parameters of the Amsterdam and Manchester models are the same, was rejected at a 99% significance level. The TTS results for the null hypothesis are binary, meaning that the transferability of the entire model is either accepted or rejected. Most previous studies that assess transferability through TTS measure produce results rejecting the null hypothesis. This limitation of the TTS measure is addressed with TI and RMSE measures, which consider transferability as a continuous measure. The results of *naïve transferability* as assessed through TI and RMSE measures is illustrated in the figures below:

Fig. 4 illustrates that the mixed logit model significantly outperforms the MNL model in terms of TI values. The TI value of the MNL model stands at −0.3, indicating that the Amsterdam MNL model performs even worse than a market share model (a model with constants only) when transferred. Whilst most transferability studies report positive TI values, it is worth noting that negative TIs can occur, as observed by (Sikder et al., 2014). In contrast, the mixed logit model demonstrates superior performance over the MNL model with a higher TI value of 0.6. This could be interpreted to mean that a naively transferred mixed logit model can capture 60% of the overall behaviour as explained by the Manchester model, which was estimated using Manchester data. Moving to Fig. 5, we observe RMSE values for the transferred MNL and ML models. Once again, the ML model outperforms the MNL model, having a lower RMSE value. However, in contrast to disaggregate measures (TI values), the MNL model's performance in the aggregate measure (RMSE) remains relatively comparable to that of the mixed lofit model.

Table 5
Naïve transferability - TTS.

	MNL	Mixed logit
LL (Bi)	−1034	−1048
LL (Bj)	−1395	−1395
TTS	723	694
Parameters/df	35	37
p-value	Less than 0.00001	Less than 0.00001
Result	Null hypothesis is rejected	Null hypothesis is rejected

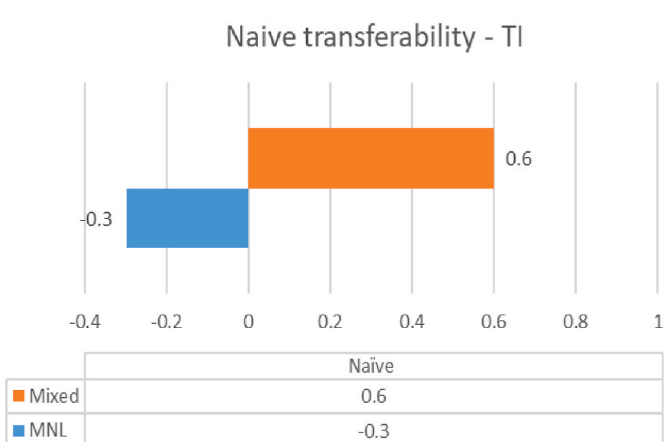

Fig. 4. Naive transferability - TI.

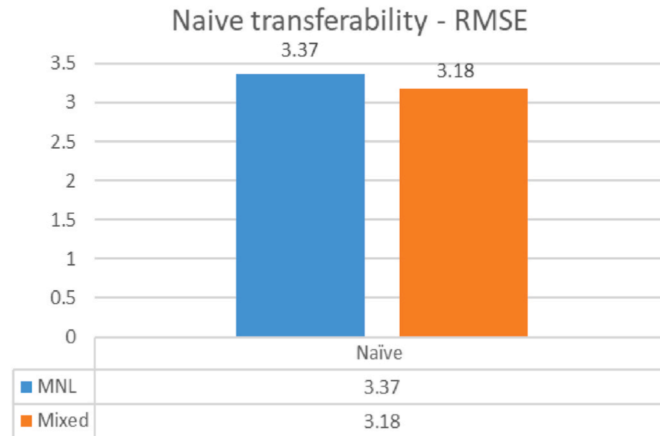

Fig. 5. Naive transferability - RMSE.

5.2. Other transfer procedure

Other transfer methods involving scaling and updating the ASC were employed and were compared to results obtained through the naive transfer as reference. The scaling procedure adjusts for variations between the two contexts. In the scaling transfer approach, the scaling factor for the Amsterdam model was determined in relation to Manchester, establishing Manchester as the reference point for scaling. Essentially, after scaling, the parameters of the Amsterdam model become comparable to those of Manchester, as the variation in both models is standardized. All the parameters of the Amsterdam model (except for the ASC) were multiplied by this estimated scale factor and transferred them to the Manchester dataset, as shown in the equation below:

$$V_m^A = ASC_t + \lambda * \beta_t * X_{im}^A$$

λ is the estimated scale parameter.

Notably, the estimated scale for Amsterdam models is less than 1, indicating a greater unexplained variance in the Amsterdam dataset as compared to the Manchester dataset.

In another transfer procedure, adjustments were made to the ASC values in the Amsterdam models to accommodate variations in mode preferences attributed to unexplained factors. In the MNL model, the constant ASC terms were updated, while in the ML model, the mean of the distribution of ASC terms was updated. The ASC values were updated to imitate the mode shares observed in the Manchester data, as illustrated in the following equation:

$$V_m^A = ASC^A + \lambda * \beta_t * X_{im}^A$$

ASC^A is the updated ASC based on the application context.

The consolidated results for all transfer procedures assessed through the TI Fig. 6, where *naïve transfer* values serve as a reference point. The scaling procedure elevated the TI value from 0.6 to 0.72 for the ML model, while for the MNL model, it increased to −0.1 from −0.3, as shown in Fig. 6. However, updating the ASC did not yield significant improvements in TI values. The most substantial TI values were achieved when both scaling, and ASC updates were applied simultaneously to the ML model. A scaled ML model with an updated ASC value explains 75% of the overall behaviour, compared to 60% in the case of naïve transferability. Although no universally accepted threshold defines good transferability, the results presented in this paper are comparable to those found in other published studies (Fox et al., 2014; Sikder et al., 2014).

Similar outcomes were observed for RMSE values, as shown in Fig. 7. After scaling, the RMSE values fall to 2.87 from 3.18 for mixed logit model, whereas for MNL the relative drop was smaller. Updating the

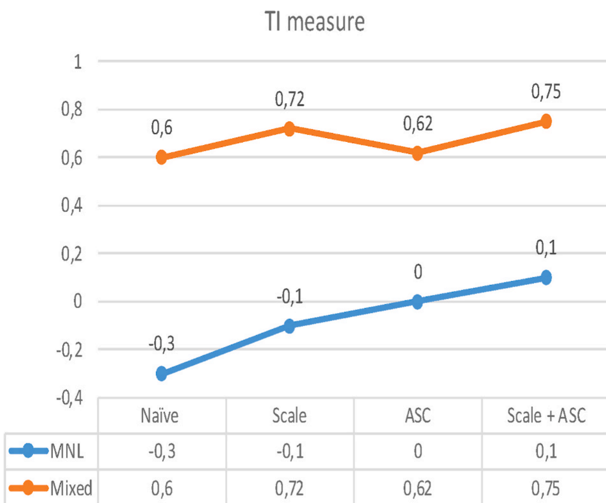

Fig. 6. TI measure.

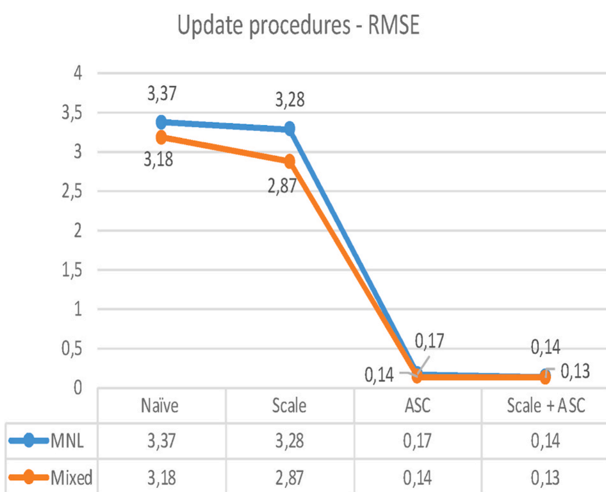

Fig. 7. RMSE measure.

ASC resulted in a significant reduction in RMSE values for both models, where the values fell to 0.17 and 0.14 for MNL and mixed logit model respectively. This aligns with findings reported in other published studies (Koppelman and Wilmot, 1982), which reported similar huge improvements in RMSE values after updating ASC. The ASC update procedure uses observed aggregate mode shares from the application context for updating, resulting in improved performance in terms of aggregate assessment measures such as RMSE compared to other procedures. Similar to the TI measure, the scaled ML model with updated ASC values demonstrates the best performance in RMSE measures, limiting errors in aggregate mode share predictions to 0.13. The observed and predicted mode shares after updating ASC and scale for a mixed model are almost same as shown in Table 6.

Table 6
Observed and predicted mode share.

	Observed (%)	Predicted (%)
Status Quo	79	79
Shared Electric Vehicle	9	10
Shared Electric Bike	12	11

5.3. Behavioural differences

In preceding sections, we discussed the overall efficiency of transferred models in explaining the behaviour in the application data. Furthermore, it is crucial to discern which parameters of transferred models effectively account for behaviour and which do not, through comparison with the parameters of the application context model (the Manchester model). This exercise is critical from the policy perspective as it acknowledges the fact that there will always exists true behavioural differences which even the '*best transferred*' model may not explain. Since in our context, the scaled mixed logit model with an updated, ASC performed best in both disaggregate and aggregate transferability measures, it was further examined with additional analysis on the individual model parameters.

The parameters for the transferred model were compared with the parameters of the Manchester model using an individual parameter *t*-test at a 95% confidence interval threshold following the equation:

$$t = \frac{M_1 - M_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where M_1 and M_2 represent the mean values of the estimated parameters being compared, s_1 and s_2 denote their respective standard deviations, and n_1 and n_2 indicate the corresponding sample sizes. The parameters that statistically differ in both the models are listed in Table 7.

The analysis reveals statistically significant differences in the standard deviation for SEB and SEV. This suggests variations in the heterogeneity surrounding the average preference for SEV and SEB in both cities. Specifically, the higher absolute standard deviation implies more heterogeneity in average preferences towards shared electric vehicles among Manchester respondents compared to those in Amsterdam. Furthermore, discrepancies were observed in another set of parameters related to the Level of Service (LOS) attributes of eHUBS, such as access time, travel time, and cost of service. Manchester respondents exhibited higher sensitivity towards these attributes, indicating a greater disutility for eHUBS as access/egress time, travel time, and service costs increased compared to their counterparts in Amsterdam. Additionally, when it comes to the preferences towards continuing to use their current modes, the sensitivities for parking search time differ in both the cities.

The insights derived from this comparison could be valuable in designing eHUBS. For instance, respondents in Manchester show a higher sensitivity to access and egress time compared to those in Amsterdam (−0.16 vs. −0.04). To ensure a higher mode share of eHUBS in Manchester, it is crucial to accommodate these preferences by increasing the density of hubs, thus minimizing access and egress times. This strategy is more effective than extending coverage into new areas, which could increase access times for these new hubs. Similarly, Manchester respondents display a higher sensitivity to parking search time for current modes. This suggests that eHUBS in Manchester should be

Table 7
Individual parameter with differences.

No	Parameter name[a]	Manchester estimates	Transferred estimates	t-value	p-value
1	SEB: standard deviation	3.72	−2.09	12.35	0.00
2	SEV: standard deviation	−3.62	−2.25	2.93	0.00
3	SEB: Access/ Egress time	−0.16	−0.04	2.56	0.01
4	SEV: Access/ Egress time	−0.15	−0.02	5.15	0.00
5	SEB: Travel cost	−1.35	−0.27	6.23	0.00
6	SQ: Parking search time	−0.45	−0.07	2.83	0.00
7	SEB: Travel time	−0.14	−0.03	3.39	0.00

[a] SEB – Shared Electric Bike, SEV – Shared Electric Vehicle, SQ – Status Quo.

large enough to avoid parking wait times. In conclusion, tailoring mobility hubs to accommodate the observed preferences of respondents, as indicated by the transferability analysis, can enhance the effectiveness of eHUBS. The eHUBS can be tailored to accommodate the preferences from the range of available options as described by (Hachette & L'Hostis, 2024).

6. Discussions and conclusions

This study sought to test the spatial transferability of a mode choice model developed in one context (Amsterdam) to another (Manchester). While the present study focused on the use of eHUBS, the results have broader implications for transportation planning, demonstrating the value of transferring and applying developed models to new contexts, thus saving a substantial amount of time and resources. Based on the results presented above, we wish to highlight several noteworthy observations, limitations and future avenues of research and conclusions from the research presented in this paper:

6.1. Notable observations

Superior performance of mixed logit model: In most cases, the superior performance of the mixed logit model compared to the MNL could be attributed to its flexible structure, which incorporates a parameter distribution to account for preference heterogeneity among respondents (Hess and Train, 2017) as well as the panel effect that addresses the correlation between multiple responses from the same individual in the data. This flexibility likely contributes to its enhanced transferability.

Difference in performance between disaggregate and aggregate measures: A range of performance levels of the same model was observed when assessed using disaggregate (TI) and aggregate (RMSE) measures. This raises the question of how to proceed when results from different assessment measures diverge. In such instances there are two factors that could be considered; firstly, it is essential to consider the robustness of the assessment in drawing conclusions regarding transferability. As emphasized by (Forsey et al., 2014), aggregate measures tend to be less robust compared to disaggregate measures. This is because a model's capacity to predict choices at the aggregate level may not necessarily reflect its performance in disaggregate assessments. Secondly a factor to consider is the intended purpose of model transfer. If the primary objective of model transfer is to accurately predict aggregate behaviour in the application context, aggregate measures such as RMSE may carry more weight. Conversely, when the aim is to comprehend behaviour and analyse policy impacts in the application context, disaggregate measures such as TI may prove more valuable.

Policy considerations: The results from individual parameter comparisons showed that the transferred model effectively captures behaviour in the application context, with notable exceptions of a few parameters. These exceptions may be attributed to genuine behavioural differences between the two cities. From a policy perspective, it is crucial to acknowledge that whenever a model is transferred to another context for predictive purposes, there could be actual behavioural differences that the transferred model may not fully explain. Therefore, any policy interventions based on the transferred model should incorporate a caveat regarding these "*non-explainable*" behavioural variations. Such recognition ensures that policy decisions are grounded in an understanding of local contexts and realities.

6.2. Limitations and future research scope

Interplay between transfer procedures and assessment measures: Previous studies have explored transferability, however, research on the relationships between transfer procedures and assessment measures remains limited (Sikder et al., 2013). Our results indicate that the scaling procedure improves the disaggregate assessment measure (TI), while updating the ASC enhances the aggregate assessment measure (RMSE). This finding offers an initial indication about the relationships between transfer procedures and assessment measures, however, an intriguing avenue for future investigation lies in the analysis of factors that can influence the nature of this relationship, although this topic is beyond the scope of the current paper.

Modelling specific gaps in transferability: We would like to highlight a few gaps in transferability research specific to modelling structure that can be explored in the future. Firstly, regarding the data types and its implication on transferability. The current study is based on stated preference data, the limitation of which is well established in terms of hypothetical bias that it may possess. An interesting question arises as to how the transferability varies for other data types such as the revealed preference data vis-à-vis the stated preference data. The second research gap is the transferability of other types of models. The current and the previous research project focused on the MNL and mixed logit model, however, alternative model structures such as error component logit (relaxing independence assumption and allowing correlation between alternatives), latent class (Delbosc and Naznin, 2019), and hybrid choice models (Vij et al., 2013) have not been tested for their transferability. Exploring whether these models, known for their robust fit within estimation contexts, can better explain behaviour when transferred to unfamiliar data sets presents an interesting avenue. The third gap relates to analysing the implication of different specifications (eg: Espino et al. (2006); Vega et al. (2018)) in the utility on transferability. While our paper adopts a linear in parameter utility specification, alternative specifications, including nonlinear formulations and variable interactions, offer ground for future exploration.

Extending transferability from policy perspectives: While we focused on model transferability and individual parameter comparison, there exists an opportunity for further extension through policy-specific transferability analysis (Parady and Axhausen, 2023). This requires examining the response to policy scenarios by comparing elasticities in both contexts. We would recommend the paper by (Sikder et al., 2014) for researchers who would wish to extend transferability analysis for policy scenarios.

Alternative approaches in model transferability: A final aspect of limitation concerns the unexamined alternative approaches in model transferability within the current study. Specifically, we did not investigate the impact of pooled data (joint estimation) on transferability, primarily due to data being available from only two spatial contexts. With access to data from more than two sources, the possibility of pooling two data sources and subsequently examining transferability across the remaining ones would have been feasible. The inclusion of more diverse data sources can potentially enhance transferability by incorporating context-specific variables that better encapsulate local characteristics. Another approach that was not included in this paper is the Bayesian methods in the domain of model transferability. While our present study predominantly revolves around classical statistical methodologies in transfer procedures, the adoption of Bayesian approaches also could be considered. Several previous studies have adopted Bayesian approaches in transferability (Nohekhan et al., 2022), however, it is recommended to employ Bayesian approaches primarily in situations where there is an anticipation of the transfer bias between the two contexts is less, as suggested by (Karasmaa, 2007).

6.3. Conclusions

The concept of transferability in choice models offers a promising avenue for mitigating the challenges associated with data collection and the expenses incurred during model development. Our study explores the transferability of MNL and mixed logit models, initially developed to understand travel behaviour in the context of eHUBS in Amsterdam and assessing their applicability in explaining travel behaviour within the framework of a different city Manchester. We employed four distinct transfer procedures and evaluated their efficiency employing three assessment measures. The results of the transferability analysis indicate that a scaled mixed logit model with an updated ASC can effectively account for 75% of behaviour in the application context and reduces prediction errors to 0.13. Another noteworthy finding uncovered in our analysis is that the scaling procedure leads to improvements in the disaggregate assessment measures TI, whilst updating the ASC results the enhanced aggregate assessment measure namely RMSE. Following the analysis, the paper presents an in-depth discussion of the transferability results and their implications for future research. This discussion aims to provide a nuanced understanding of transferability analysis. More specifically we delve into topics such as the transferability of models at both aggregate and disaggregate levels, the enhanced transferability observed in mixed logit models, the intricate relationship between transfer procedures and assessment measures, and the potential generalization of transferability results. These discussions offer valuable insights for researchers planning future studies and offer practical considerations for policymakers.

CRediT authorship contribution statement

Kuldeep Kavta: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Gustav Bösehans:** Writing – review & editing, Data curation. **Margaret Carol Bell:** Writing – review & editing, Supervision, Project administration. **Fanchao Liao:** Writing – review & editing. **Gonçalo Homem de Almeida Correia:** Writing – review & editing. **Dilum Dissanayake:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation.

Data availability

The authors do not have permission to share data.

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