European Transport Studies 2 (2025) 100030

Contents lists available at ScienceDirect

European Transport Studies

journal homepage: www.sciencedirect.com/journal/european-transport-studies

Electric vehicle charger sharing services: a latent class analysis based on private charger owners' motivation and intention to share as hosts

Yanghui Cao, Yuerong Zhang *

Energy Institute, University College London, 14 Upper Woburn Place, WC1H 0NN, London, United Kingdom

ARTICLE INFO

Keywords:
Shared mobility
Electric vehicle charging
Public attitudes
London

ABSTRACT

As the global adoption of electric vehicles (EVs) accelerates, the need for accessible and scalable charging infrastructure poses a growing challenge, particularly in urban areas. While research has largely focused on public charging provision, the potential of private charger sharing – facilitated through Charger Sharing Services (CSS) remains underexplored. This study investigates the factors shaping private EV charger owners' willingness to participate in CSS, using survey data from London-based charger owners. Latent Class Analysis was employed to segment respondents based on their economic, social, and moral motivations, as well as their intention to share. Four distinct consumer segments were identified and are presented in conceptual order from least to most motivated to share: Unmotivated Reluctant, Indifferent, Economic-Centred, and Highly Motivated. Each segment reflects unique socio-demographic and travel behaviour profiles. Results show that economic motivations play a pivotal role especially among those who are younger and cost-conscious, whereas wealthier and more highly educated groups exhibit greater reluctance. These findings point to the importance of tailored engagement strategies. Policy and industry recommendations are offered to strengthen CSS adoption in the host side and support more connected, equitable EV charging networks.

1. Introduction

As the global urgency to mitigate climate change intensifies, the transportation sector has emerged as a critical target for sustainability efforts, responsible for nearly 24 % of global CO_2 emissions from fuel combustion (International Energy Agency (IEA), 2023a). A significant step in reducing emissions is the rapid adoption of electric vehicles (EVs), a sustainable alternative to internal combustion engine vehicles. This transition is accelerated by international commitments, such as the European Union's target of net-zero emissions by 2050 and the UK's ban on new petrol and diesel car sales by 2035. Global EV sales surged to approximately 10 million units in 2022—a 55 % increase from 2021 (International Energy Agency (IEA), 2023b). While EVs offer considerable benefits, such as reducing emissions and indirectly improving public health, their widespread adoption is significantly constrained by the limited deployment of charging infrastructure, particularly in densely populated areas where space for installing public EV chargers is either insufficient or prohibitively expensive (Budnitz et al., 2024; LaMonaca and Ryan, 2022). To accommodate the growing number of EVs, a robust and diverse network of charging facilities is essential to meet the varying needs of users (Hopkins et al., 2023). Despite an increase in public chargers in the UK, from 9000 in 2016 to nearly 45,000 in 2023 (Department for Transport (DfT), 2022), demand still outpaces supply, especially in urban areas where suitable locations and expansion costs are major barriers (Greene et al., 2020; Hopkins et al., 2023). In London, fewer than 50 % of households have access to private driveways or garages (Budnitz et al., 2024), which inevitably pose restriction to have their own EV chargers installed even though the public charger are less accessible (Li and Guo, 2014).

To date, most research has focused on public charging infrastructure, covering a wide range of topics, including the relationship between EV adoption and accessibility (Falchetta and Noussan, 2021), charger accessibility and equity (Zhang et al., 2024; Zhang and Kamargianni, 2023), charger placement and site optimisation (Charly et al., 2023), and the resilience of urban charging infrastructure against blackouts and flooding (Essus and Rachunok, 2024; Raman et al., 2022). As the understanding of public charging networks grows, it has become increasingly clear that they face significant limitations. These include space requirements and financial and logistical barriers, such as high upfront costs, complex regulations, and the need to meet diverse technical and

* Corresponding author.
E-mail address: yr.zhang@ucl.ac.uk (Y. Zhang).

https://doi.org/10.1016/j.ets.2025.100030

Available online 15 August 2025

2950-2985/© 2025 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

user demands (Dixon et al., 2020; Budnitz et al., 2024). To build a connected and reliable charging network, it is crucial to explore new models that can complement public EV charging infrastructure effectively, ease the pressure on public chargers and enhance grid stability (Chen et al., 2020).

Against this backdrop, Charger Sharing Services (CSS) have emerged as a peer-to-peer model that allows private charger owners to make their home chargers available to other EV users via digital platforms. Several UK-based start-ups (e.g., co charge, Joosup) have pioneered this model, referred to in this paper as CSS (Co-Charger, 2024; Joosup, 2025). These business models typically operate within closed ecosystems, and facilitate temporary access to privately owned chargers. This shared functionality informed our working definition of CSS as a peer-to-peer service model surrounding privately-owned EV chargers. In this context, following the terms used in industry, we refer to private charger owners who make their charging points available for others as "hosts", while "chargees" are electric vehicle users who access and use these chargers through the sharing platform. Throughout this paper, we use these terms to distinguish between those providing charging access and those receiving it, aligning with common terminology in the peer-to-peer mobility literature.

While CSS offers a promising way to reduce pressure on public infrastructure and expand access, its success depends on whether hosts are willing to participate. Yet, little is known about who these prospective hosts are, and what motivates them. This study contributes to the growing body of literature on EV charger sharing by providing empirical insights into the motivations driving hosts' willingness to share their private charging facilities. By applying a latent class analysis framework, we uncover four distinct consumer segments and identify the underlying motivational factors. Identifying these segments is critical for understanding consumer decision-making and developing corresponding strategies that facilitate sharing intention of each group. This study is the one of the first to focus specifically on understanding these motivations and intention to share from the hosts' perspective in the London context. Actionable insights for policymakers and industry stakeholders were provided based on our findings to facilitate charger sharing participation and alleviate the pressure on public charging networks to match the growing demand of EV charging.

2. Literature review

2.1. EV charger sharing models

In the literature on shared EV chargers, efforts have been made to apply the concept of the sharing economy to charging infrastructure, with the aim of easing pressure on public charging networks. These studies can generally be divided into two strands: one focusing on co-owned or community-shared chargers, and the other on privately-owned chargers being shared with others. The first strand that attract more attention from scholars, a central topic is its economic benefit, such as by sharing community-owned EV chargers to external users, and co-owned EV chargers financed and used by multiple households. For instance, research by Azarova et al. (2020) promotes community-owned EV chargers, which helps to democratize access to charging infrastructure and supports equitable mobility solutions, as well as earning the communities or the hosts with economic benefits. Similarly, Velkovski et al. (2024) and Gong et al. (2019) focus on 'tweaking' the ownership of chargers. By spreading the cost among several households, this shared ownership can help reducing the initial investment and benefit the hosts. These studies promote the concept of collective ownership, thereby sharing the investment and economic benefits among communities' members and households. However, as some authors point out (e.g., Velkovski et al., 2024), these economic benefits may come at the cost of reduced charging flexibility for internal users.

While community-owned or co-owned charging models reduce upfront investment per user, they frequently face challenges related to access coordination—particularly when several users wish to charge their vehicles at the same time, leading to potential conflicts and inconvenience. In contrast, private charger sharing is organised on a peer-to-peer basis: individual hosts make their own home chargers available to chargees, but retain full control over when and how their charger is offered. This flexibility enables hosts to avoid overlapping charging demand, since they can set availability according to their personal schedules and preferences. This approach not only improves charger utilisation but also offers a potential revenue stream for hosts (Plenter et al., 2018; Hu et al., 2021; Yang et al., 2024). By enabling collaborative consumption through digital platforms, CSS represents a flexible and scalable complement to traditional infrastructure (Zervas et al., 2017). These platforms allow hosts to set availability, pricing, and usage terms, while managing bookings and access control through mobile apps. Due to the nascent market uptake, relatively few studies have examined this sharing model in a consumer adoption context (Cao et al., 2025). Most have instead centred on simulation – either adoption rates or corresponding benefits of adoption. For example, Plenter et al. (2018) used a survey study to estimate the proportion of German charger owners willing to participate as CSS hosts, focusing on the potential for increased charger utilisation and supplementary host income. Matzner et al. (2018) taken the benefit simulation further, which propose that integrating private chargers into the public EV charging network could reduce infrastructure investment and enhance network connectivity. Similarly, Hu et al. (2021) simulated the potential saving that private hosts can get by participating in CSS.

Although these studies presented and emphasised the infrastructural and individual level of benefits for CSS mass adoption, an individual vision was missing – it is yet known about the factors that influence charger owners' sharing decision. As a key prerequisite to facilitating the adoption of shared charging models, especially in context of CSS given its nascent phase of development and market penetration, this information can help promoting private charger sharing. Understanding these influencing factors is crucial for promoting private charger sharing and informing targeted interventions. Therefore, this study aims to provide such knowledge and bridge the gap in literature of this nascent sharing economy model.

2.2. Motivational factors influencing sharing decisions of private owners

Motivations are central constructs in understanding behaviour, particularly in the context of travel and tourism. Understanding motivations is central to explaining engagement with shared mobility services, which form a key part of the modern transport landscape. Shared mobility encompasses a range of services (e.g., ride-hailing, car-sharing), that allow users to access vehicles or infrastructure without private ownership, often via digital platforms. These services belong to the broader sharing economy, where behaviour is driven by economic, social, and moral considerations (Hamari et al., 2016; Botsman and Rogers, 2010).

Among these three motivations that were frequently investigated in past sharing economy studies, economic motivations remain a critical driver in shared mobility contexts. Economic motivation refers to the extent to which individuals are driven by financial incentives, cost recovery, or asset monetization. Platforms such as Airbnb and Uber provide cost-effective alternatives to hotels and taxis respectively, which attract individuals seeking to maximise value for money (Böcker and Meelen, 2017). The potential for lower travel costs, reduced ownership responsibilities, and monetisation of underutilised assets has been consistently identified across sectors such as car-sharing (Magno, 2021), e-scooter use (Guo and Zhang, 2021), and peer-to-peer EV charger sharing (Plenter et al., 2018). In the case of CSS, hosts can host chargees, leveraging idle capacity for supplementary income. However, purely economic framing can be short-lived. For instance, research by Zeiske et al. (2021) and Tussyadiah (2015) caution that financial incentives may only momentarily boost participation if deeper motivational factors are not nurtured. Such discrepancies in findings highlight the need to clarify the role of economic motivation for sharers in the specific context of CSS.

Economic motivation alone may not represent the full profile shape individuals' decision (Hamari et al., 2016). That is, adopting sharing mobilities also provides the social opportunities for the sharers, to form social ties and accompany by participating in CSS (Kaushal and Prashar, 2022). Social motivation captures the extent to which individuals are influenced by opportunities for social interaction, peer recognition, or contributing to a sense of community (Böcker and Meelen, 2017; Kaushal and Prashar, 2022). Research on other peer-to-peer platforms has shown that many hosts value interactions with guests and gain social fulfilment through sharing (Bucher et al., 2016; Tussyadiah and Pesonen, 2016). Böcker and Meelen (2017) describe how social returns such as trust-building and reciprocal goodwill can enhance sharing motivation, particularly in local community contexts. In CSS, these motivations may be salient for early adopters who view their participation as part of a broader movement toward sustainable mobility and cooperative urban living.

Lastly, moral motivations constitutes sustainability, altruism and pro-environmental concerns, and have gained traction in shared mobility studies. For instance, researchers highlight that moral norms can significantly shape willingness to adopt innovative solutions, particularly in sustainability transitions (Hamari et al., 2016; Leismann et al., 2013). That is, while economic motivations often initiate engagement, sustained sharing behavior may require alignment with moral values (Bucher et al., 2016). This perspective is particularly relevant in the travel sector, where individual may opt for ride-hailing services or shared accommodations not just for convenience but also for their perceived contribution to an eco-friendlier form of travel (Elnadi and Gheith, 2022). For charger owners, this includes the belief that sharing contributes to equitable EV access or helps others without home charging options. However, in the specific context of CSS, as a nascent practice in the UK which have been limitedly marketed as a specific environmentally friendly practice, a broader moral motivation (e.g., personal responsibility, concern for others) may nonetheless encourage hosts to participate (Bucher et al., 2016).

Notably, despite the prominence of economic, social, and moral motivations in the sharing economy literature, most studies to date have examined these constructs in relation to users or adopters—those who access or consume shared services. In contrast, fewer studies have systematically investigated hosts or service providers (platforms), who make their personal assets available for use by others. While some work has begun to explore supply-side participation (e.g., Plenter et al., 2018), these remain exceptions. Thereby, this research also aims to addresses the gap in supply-side sharing literature and offers new insights into emerging peer-to-peer infrastructure models.

Taking together, we focus on three key motivational constructs in this study to examine charger owners' intention to participate in CSS. While no single theoretical framework currently supports this three-fold motivational typology, this study draws from conceptual strands in shared mobility and collaborative consumption literature that consistently highlight these as dominant constructs. This selection is grounded in a substantial body of literature on the sharing economy and especially shared mobility, where these three domains consistently emerge as dominant dimensions influencing user behaviour (Hamari et al., 2016; Zhang and Kamargianni, 2024). Economic motivation reflects utilitarian drivers such as income generation or cost savings, social motivation captures the role of community connection and social recognition, while moral motivation reflects normative values like environmental concern or helping others (Böcker and Meelen, 2017). These constructs span the spectrum from self-interest to altruism, which offers a parsimonious framework for segmentation analysis. While other motivational factors (e.g., hedonic, trust-based) may also influence behaviour, the inclusion of these three domains offers a broader and explorative perspective for understanding early-stage adoption of CSS in the UK.

3. Methods

3.1. Sample and measure

The survey data were collected in July 2024 using Prolific, a research platform widely employed for academic studies in the social sciences. The use of Prolific allows for efficient recruitment of niche populations that may be otherwise difficult to reach using traditional sampling methods, thus enhancing the reliability and relevance of the collected data. Respondents were selected based on three inclusion criteria: 1) being aged 18 or above, 2) residing in London, and 3) currently owning a private home charger. London was selected as the study site due to its high concentration of EVs, limited availability of off-street parking (and EV charging), and growing interest in alternative charging solutions (Zhang and Kamargianni, 2024). As a dense, policy-active urban region with significant charging infrastructure pressures, London offers a relevant context for examining the feasibility and adoption of Charger Sharing Services.

To gain a comprehensive understanding of charger owners' socio-demographic profiles and their intention toward participating in CSS as hosts, the questionnaire survey consists of three sections: 1) Demographic variables, 2) Travel behaviour, and 3) Motivational drivers (i.e. economic, social and moral motivations) and intention to participate in CSS as a host. Notably, prior to the motivational drivers and intention to share section, we shown all participants a designed brief message to introduce the concept of CSS: *Charger Sharing Services (CSS) let private EV charger owners to 'rent out' their chargers to other EV users, often arranged through an app or website (just like Uber and Airbnb)*. All responses were collected at the individual level; that is, each participant self-reported their demographic details, travel behaviours, motivations, and intention to share, independent of other household members. Descriptive statistics for participants' characteristics are presented in the Table 1 below. The final sample (N = 604) was characterised by a relatively high socio-economic status, with the majority holding at least a bachelor's degree, more than three-quarters in full-time employment and over a third of respondents reported annual household incomes above £ 45,000.

Measures for motivational and behavioural items were adopted from previous literature (Bucher et al., 2016; Bak et al., 2022; Lamberton and Rose, 2012) and were pilot tested online before official data collection to ensure the validity and accuracy. All latent constructs were measured using five-point Likert scale items, where Respondents rated their agreement with each item from 1 (Strongly Disagree) to 5 (Strongly Agree), consistent with prior studies in past literature. To further ensure the validity and reliability of the measurement model, a confirmatory factor analysis (CFA) was conducted using Mplus, a statistical modelling software, to test if the items contribute to the constructs representing different motivations (Brown, 2015; Brown and Moore, 2015). Table 2 shows the factor loading of adapted items. All observed items demonstrate satisfactory loadings on their respective latent factors, with loadings ranging from 0.830 to 0.964 (Marsh et al., 1988). The model fit indices also indicate an excellent fit based on the indices suggested by literature (CFI = 0.987, TLI = 0.982, and SRMR = 0.024) (Brown and Moore, 2012).

3.2. Latent class analysis

To identify distinct owner segments within the context of CSS, Latent Class Analysis (LCA) was chosen. LCA is used because it allows to model heterogeneity in the population and categorise individuals into distinct classes based on shared characteristics (Muchlisin et al., 2024). The resulting clusters represent subgroups within the population that share similar motivational profiles, thereby providing actionable insights for policymakers and businesses seeking to tailor their engagement strategies. The validity of these segments was assessed through model fit indices and interpretive consistency with previous research on sharing

Table 1
Participant characteristics.

	Full sample (percentage)
Gender	
Male	57.80 %
Female	40.70 %
Others	1.50
Education	
GCSE or equivalent	4.80
A-levels (high school)	16.90
Bachelor's degree	48.70
Master's degree	25
Doctoral or professional degree	3.8
Others	0.9
Employment	
Full time	78.3
Part time	12.4
Student	4.6
Unemployed	3.6
Retired	1
Income	
less than £ 5,000	3.6
£ 5,000- £ 14,999	6.1
£ 15,000- £ 24,999	11.6
£ 25,000- £ 34,999	25.3
£ 35,000- £ 44,999	17.9
above £ 45,000	35.4
Number of adults household	
One	16.7
Two	60.4
Three	13.7
Four or more	9.1
Number of children household	
None	52
One	20.9
Two	20.7
Three or more	6.5
Tenure	
Owner-occupied	59.1
Privately rented	32.1
Socially rented	5.1
Shared ownership	3
Other	0.7
Dwelling	
Flat	26.2
Detached house	20.5
Semi-detached house	34.8
Terraced / End of terraced	16.9
Cottage / Bungalow	1.7
Age (Mean)	35.98
Years of Driving (Mean)	14.59

economy behaviours. This method aligns with our research question, which helps reveal patterns that may not be evident from traditional statistical approaches (Vermunt, 2002). It is also widely adopted in the field of shared mobility studies (Chahine et al., 2024; Wang and Shen, 2024; Alonso-González et al., 2020).

Furthermore, to better understand the underlying structure of the data, we used regression-based factor scores derived from confirmatory factor analysis (CFA). These scores were then used in the LCA to improve the robustness of the classification by accounting for measurement error, following the approach of past studies that adopted the same method (e.g., van't Veer et al., 2023 Skrondal and Rabe-Hesketh, 2004). The selection of the method ensure that this study allow for the inclusion of latent constructs in the LCA while accounting for measurement error, thus offering a more precise classification (Muthén, 2002; Muthén and Muthén, 2000). The entire process was completed In Mplus. To identify the optimal number of clusters, we applied and compared several model specifications from one class to five classes (see Section 4.1).

The latent class cluster model with continuous indicators and covariates can be formally expressed as follows (following Molin et al., 2016; van't Veer et al., 2023):

Table 2
Factor loading for the motivation items.

Items	Factor 1 (Economic Motivation)	Factor 2 (Social Motivation)	Factor 3 (Moral Motivation)	Factor 4 (Intention to share)
I think EV charger sharing is a good way to supplement my income.	0.884			
Earning extra money is an important factor for me to share my private EV charger.	0.83			
I will use EV charger sharing because it helps me pay my bills.	0.923			
Using charger sharing would allow me to get in touch with people who share my interests.		0.897		
Using charger sharing would allow me to get in touch with people who think like me.		0.919		
Sharing makes me feel part of a community.		0.874		
Sharing is a good way to meet new people.		0.861		
I share because I feel a moral obligation to help others.			0.849	
EV charger sharing makes me think that I am doing something meaningful.			0.920	
Sharing my charger to those who need is a decent choice.			0.877	
I plan to share my charger with others in the future				0.954
If the circumstances allow it, I will share in the future.				0.939
I intend to share my charger in the future				0.964

$$f(y_i \mid z_i^{cov}) = \sum_{x=1}^{K} P(x \mid z_i^{cov}) \prod_{m=1}^{M} f(y_{im} \mid x) \quad (1)$$

In this formulation, x represents the latent categorical variable, and K represents the total number of latent classes. Each individual i is associated with a vector (their responses) of covariates z_i^{cov}, which influences their probability of class membership. The structural model is represented by the term $P(x| \ z_i^{cov})$, this part estimates the probability that individual i belongs to latent class x given their covariates z_i^{cov}, and are modelled using a multinomial logit framework (van't Veer et al., 2023). The measurement model is represented by $\prod_{m=1}^{M} f(y_{im} \quad |x)$, which describes the probability density of the individual's response y_{im} to m (indicators), where M is the total number of indicators. Together, these components define the joint likelihood of an individual's response pattern as a mixture of class-specific indicator distributions, weighted by the class probabilities conditional on covariates (Vermunt, 2002).

In practical application, LCA estimation proceeds in two parts. First, the measurement model identifies latent clusters based on response patterns to a set of indicators. A model is considered well-fitting when BIC and AIC are minimized and entropy is high, which will be further elaborated in Section 4.1 (Vermunt, 2002). Next, the structural model estimates how class membership probabilities vary as a function of selected covariates. Specifically, after the number of classes was determined, the structural model (or called membership model) is estimated by adding the covariates. All socio-demographic and behavioural covariates were initially included in the latent class model. Following established practice (Molin et al., 2016; van't Veer et al., 2023), only those covariates with a Wald statistic larger than 3.84 ($p < 0.05$) were retained as active predictors of class membership. Covariates that did not meet this criterion were treated as inactive covariates, and were used for descriptive profiling but not for class formation (Molin et al., 2016).

Fig. 1 presents the proposed relationship among the indicators, active and inactive covariates included in analysis. In the measurement model, we selected three key motivational dimensions as indicators that drive the intention to share EV chargers, namely economic, social, and moral motivations. These latent variables were derived from survey responses to capture the various motivations influencing participants' intention towards CSS. For the structural model, we incorporated active covariates that reflect travel-related characteristics, such as daily travel duration, travel distance, travel costs, the number of vehicles owned per household, EV ownership status, and primary EV trip purposes. These active covariates directly influence the likelihood of cluster membership, thus shaping the segmentation process. In contrast, inactive covariates, including socio-demographic and built environment variables such as gender, education and employment status are included to describe each cluster's characteristics without impacting cluster assignment probabilities.

4. Results & discussion

4.1. Latent class analysis

To identify latent subgroups among current private EV charger owners in London, a LCA was conducted based on participants' self-reported motivations and intentions to share their chargers. Model selection was guided by fit indices including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (SABIC), and entropy values (see Table 3). As the number of latent classes increased from one to five, both AIC and SABIC values improved consistently, indicating better model fit. Although the five-class model demonstrated the highest entropy (0.971), the increase in BIC values and diminishing marginal interpretability suggested overfitting. Consequently, the four-class model was identified as the most suitable solution, with AIC = 19,163.522, BIC = 20,180.748, and SABIC = 19,447.381. Although the five-class model slightly improved the AIC and entropy (0.971), the increase in BIC suggests that the additional complexity may not be justified (Muthén, 2002). Therefore, for parsimony and ease of interpretation, the four-class model was selected as the optimal solution.

After checking the model fit and identifying the optimal number of clusters, we then included the travel characteristics as active covariates in the model to explore whether different clusters were associated with

Table 3
Fit indices for 1- through 5-segment models.

Number of classes	Log-likelihood	AIC	BIC	SABIC	Entropy
1	−13173.07	26466.141	26730.355	26539.87	N/A
2	−11114.988	22463.976	22979.194	22607.748	0.932
3	−9921.21	20190.42	20956.642	20404.236	0.964
4	−9350.761	19163.522	20180.748	19447.381	0.968
5	−9481.947	19539.895	20808.124	19893.797	0.971

Note:
AIC = Akaike Information Criteria.
BIC = Bayesian Information Criteria.
SABIC = Sample-size Adjusted Bayesian Information Criteria.

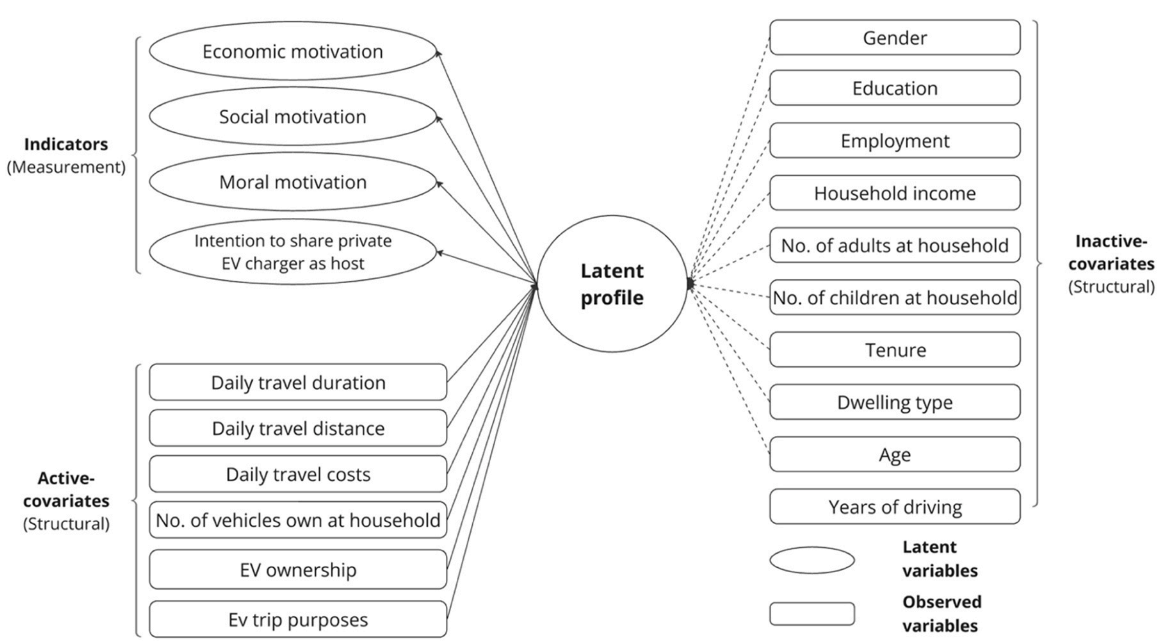

Fig. 1. Graphical representation of the motivation-intention based LCA model.

specific types of travel behaviour patterns. The four identified clusters reflect diverse motivational profiles and intentions toward participation in CSS. Table 4 presents the proportion of participants in each cluster alongside their mean factor scores for economic, social, and moral motivations, as well as intention to share. Additionally, it displays key travel-related covariates used in the LCA. To facilitate interpretation, the clusters are presented in ascending order of sharing intention: (1) Unmotivated Reluctant; (2) Indifferent; (3) Economic-Centred, and; (4) Highly Motivated. Latent classes are presented in a conceptual sequence from lowest to highest sharing motivation and intention to enhance interpretive clarity.

Notably, the "Unmotivated Reluctant" cluster constitutes 4.8 % of the sample and displays the lowest scores across all motivational domains and intention. In contrast, the "Highly Motivated" group reports uniformly high motivation and sharing intention. The "Economic-Centred" cluster comprises nearly half the sample and shows strong economic motivation but moderate scores for social and moral motivations. Meanwhile, the "Indifferent" cluster reveals mixed or muted motivations, particularly in non-economic domains. Differences in daily travel behaviour, EV usage, and vehicle ownership further distinguish these segments. For example, participants in the "Unmotivated Reluctant" group are more likely to travel short distances and rely on cost-free transport, whereas those in the "Highly Motivated" cluster tend to travel farther and spend more on transport. These travel patterns offer early cues for designing targeted engagement strategies. The following sub-sections describe each cluster in detail and interpret their socio-demographic, motivational, and behavioural profiles through the lens of shared mobility research.

4.2. Motivation-intention-based latent class profiles

Building on the previous subsection's focus on the motivational and behavioural profiles of each latent class, we now examine how these segments differ in terms of their socio-demographic characteristics. In our model, socio-demographic variables were included as inactive covariates—meaning they did not influence the formation of clusters, but are instead used here to interpret and contextualize the composition of each group. Table 5 presents the estimated distribution of these demographic features across the four clusters. Although these characteristics were not used to define the classes, their post hoc associations provide valuable insights for designing tailored policy interventions and outreach strategies.

Cluster 1 Unmotivated Reluctant (4.8 % of the sample): This small segment is characterised by the lowest motivational scores across all three domains – economic, social, and moral, as well as the lowest intention to share (see Table 4). Members of this cluster demonstrate minimal enthusiasm for CSS, suggesting strong resistance to engaging with peer-to-peer mobility platforms.

Behaviourally, this group indicates a lifestyle of predictable, cost-efficient travel patterns and potential discomfort with exposing their limited mobility resources to external use. For instance, they are featured with shortest travel durations and lowest travel expenditures, with over 58 % spending less than £ 3 per day on travel. They also show a relatively high share of commuting-focused EV use and rely

Table 4
Class membership and means of factor scores and active covariates for clusters.

	Full sample (n = 604)	Unmotivated reluctant (n = 29)	Indifferent (n = 180)	Economic-centred (n = 286)	Highly motivated (n = 109)
Proportion in sample	1	0.04	0.29	0.47	0.18
Indicators					
Economic motivation factor (Mean)	3.68	1.35	3.04	3.95	4.63
Social motivation factor (Mean)	3.35	1.09	2.37	3.30	4.31
Moral motivation factor (Mean)	3.21	1.28	2.36	3.47	4.39
Intention to share charger through CSS (Mean)	3.34	1	2.29	3.73	4.62
Active covariates					
Daily travel duration					
Less than 15 mins	14.1 %	24.1 %	16.1 %	11.9 %	13.8 %
15 –30 mins	48.0 %	55.2 %	45.6 %	48.3 %	49.5 %
30 –60 mins	33.3 %	13.8 %	34.4 %	35.0 %	32.1 %
More than 60 mins	4.6 %	6.9 %	3.9 %	4.9 %	4.6 %
Daily travel distance					
Less than 2.5 km	16.2 %	24.1 %	18.9 %	14.7 %	13.8 %
2.5 –5 km	40.2 %	31.0 %	31.1 %	48.6 %	35.8 %
5 –10 km	28.0 %	17.2 %	32.8 %	24.1 %	33.0 %
More than 10 km	15.6 %	27.6 %	17.2 %	12.6 %	17.4 %
Daily travel costs					
Less than £ 3	30.8 %	58.6 %	37.2 %	26.2 %	24.8 %
£ 3 –10	58.8 %	27.6 %	52.8 %	62.6 %	67.0 %
More than £ 10	10.4 %	13.8 %	10.0 %	11.2 %	8.3 %
Number of vehicles owned at household					
None	0.8 %	0.0 %	0.6 %	1.4 %	0.0 %
One	67.9 %	72.4 %	66.1 %	67.5 %	70.6 %
Two to three	29.8 %	27.6 %	31.7 %	29.7 %	27.5 %
More than three	1.5 %	0.0 %	1.7 %	1.4 %	1.8 %
EV ownership					
Owner	79.8 %	82.8 %	78.3 %	82.2 %	75.2 %
Use someone else's EV	12.4 %	3.4 %	14.4 %	11.9 %	12.8 %
Rental	6.6 %	10.3 %	6.1 %	5.2 %	10.1 %
Others	1.2 %	3.4 %	1.1 %	0.7 %	1.8 %
EV trip purposes					
Shopping	34.8 %	20.7 %	38.9 %	32.9 %	36.7 %
Leisure	44.4 %	44.8 %	42.8 %	48.3 %	36.7 %
Commuting	13.6 %	24.1 %	13.3 %	12.2 %	14.7 %
Business	6.1 %	3.4 %	5.0 %	5.2 %	11.0 %
Others	1.2 %	6.9 %	0.0 %	1.4 %	0.9 %

Table 5
Baseline inactive covariates for participants across the four clusters.

		Full sample (n = 604)	Unmotivated reluctant (n = 29)	Indifferent (n = 180)	Economic-centred (n = 286)	Highly motivated (n = 109)
Gender						
Male		57.8 %	72.4 %	58.3 %	54.9 %	60.6 %
Female		40.7 %	24.1 %	39.4 %	43.7 %	39.4 %
Others		1.50 %	3.4 %	2.3 %	1.4 %	0.0 %
Education						
GCSE or equivalent		4.80 %	3.4 %	0.6 %	3.5 %	6.4 %
A-levels (high school)		16.90 %	13.8 %	6.1 %	17.1 %	12.8 %
Bachelor's degree		48.70 %	48.3 %	19.4 %	50.7 %	45.0 %
Master's degree		25.0 %	6.9 %	47.8 %	25.5 %	31.2 %
Doctoral or professional degree		3.8 %	20.7 %	23.3 %	2.8 %	3.7 %
Others		0.9 %	2.8 %	2.8 %	0.3 %	0.9 %
Employment						
Full time		78.3 %	79.3 %	78.9 %	77.3 %	79.8 %
Part time		12.4 %	3.4 %	13.3 %	13.6 %	10.1 %
Student		4.6 %	3.4 %	4.4 %	4.9 %	4.6 %
Unemployed	3.6 %	10.3 %	2.8 %	3.1 %	4.6 %	
Retired		1.0 %	3.4 %	0.6 %	1.0 %	0.9 %
Income						
less than £ 5,000	3.6 %	3.4 %	3.3 %	4.2 %	2.8 %	
£ 5000- £ 14,999	6.1 %	3.4 %	5.6 %	5.9 %	8.3 %	
£ 15,000- £ 24,999	11.6 %	6.9 %	13.3 %	10.5 %	12.8 %	
£ 25000- £ 34,999	25.3 %	3.4 %	23.3 %	29 %	24.8 %	
£ 35,000- £ 44,999	17.9 %	10.3 %	16.1 %	17.8 %	22.9 %	
above £ 45,000	35.4 %	72.4 %	38.3 %	32.5 %	28.4 %	
Number of adults household						
One		16.7 %	17.2 %	14.4 %	18.9 %	14.7 %
Two		60.4 %	72.4 %	60 %	59.8 %	59.6 %
Three		13.7 %	10.3 %	17.2 %	11.9 %	13.8 %
Four or more	9.1 %	0.0 %	8.3 %	9.4 %	11.9 %	
Number of children household						
None		52.0 %	55.2 %	51.7 %	53.5 %	47.7 %
One		20.9 %	13.8 %	22.8 %	21 %	19.3 %
Two		20.7 %	27.6 %	18.9 %	19.9 %	23.9 %
Three or more	6.5 %	3.4 %	6.7 %	5.6 %	9.2 %	
Tenure						
Owner-occupied	59.1 %	75.9 %	65 %	52.4 %	62.4 %	
Privately rented	32.1 %	20.7 %	28.9 %	37.4 %	26.6 %	
Socially rented	5.1 %	3.4 %	3.3 %	6.3 %	5.5 %	
Shared ownership	3.0 %	0.0 %	2.8 %	3.1 %	3.7 %	
Other		0.7 %	0.0 %	0.0 %	0.7 %	1.8 %
Dwelling						
Flat		26.2 %	20.7 %	24.4 %	29.4 %	22.0 %
Detached house	20.5 %	20.7 %	22.2 %	18.2 %	23.9 %	
Semi-detached house	34.8 %	34.5 %	36.1 %	32.9 %	37.6 %	
Terraced / End of terraced	16.9 %	20.7 %	16.1 %	17.8 %	14.7 %	
Cottage / Bungalow	1.7 %	3.4 %	1.1 %	1.7 %	1.8 %	
Age (Mean)		35.98 %	40.7 %	36.8 %	34.7 %	36.6 %
Years of Driving (Mean)	14.59 %	19.8 %	15.2 %	13.6 %	14.9 %	

predominantly on a single household vehicle, of which they are the primary users (Table 4).

Socio-demographically, this cluster has a relatively large age and are wealthier than respondents in other clusters. With an average age of 40.7 years and 72.4 % reporting annual household incomes above £ 45,000, these participants stand apart from common profiles of sharers as described in the broader literature. This may be explained by the higher average age in this cluster, as suggested in previous studies that individuals with higher age often face barriers such as limited access to sharing economy activities or lower levels of trust to innovations (Frenken and Schor, 2019; Cherry and Pidgeon, 2018). Similarly, this tendency might also partly result from experience in other types of sharing economy activities (e.g., driving for Uber), where familiarity with the concept of sharing increases the likelihood of sharing one's private EV charger (Pellegrini et al., 2023; Chakraborty et al., 2019). Prior research in the sharing economy often links economic inactivity with increased openness to peer-to-peer platforms due to income supplementation needs (Codagnone et al., 2016; Hamari et al., 2016), but this group's disengagement suggests alternative barriers such as property boundaries, lack of trust or low familiarity with digital participation may be at impactful (Mittendorf, 2018; Hwang and Griffiths, 2017).

Furthermore, most of them are unemployed or retired, suggesting that their disengagement with CSS is not driven by lack of access or economic pressure, but potentially by lifestyle stability, risk aversion, or low perceived need. This finding is not fully aligned with earlier studies suggesting that unemployed individuals are more likely to engage in the sharing economy due to financial need (Codagnone et al., 2016; Cherry and Pidgeon, 2018). Instead, their high income and low travel cost suggest a potential perception limited marginal benefit from participating. Furthermore, their reluctance may be partly explained by discomfort with digital platform use. In the survey, CSS was introduced as a service coordinated via a mobile app or website, which may have shaped perceptions among individuals with lower digital confidence or limited familiarity with online sharing (Frenken and Schor, 2019; Cherry and Pidgeon, 2018).

In practical terms, this segment is very unlikely to respond to traditional financial incentives for participation. Potentially, targeted interventions such as trust-building initiatives or simplified app interfaces may be effective to even marginally engage this population in CSS schemes. However, for now, their contribution to shared infrastructure rollout appears limited.

Cluster 2 Indifferent (29.8 % of the sample): This cluster includes individuals with muted motivation across all three motivational domains, and their intention to share remains below the full sample average. While their economic motivation score is closer to the mean, their social and moral scores are markedly lower. These results indicate a limited connection to communal or value-driven justifications for CSS (see Table 4).

From a behavioural standpoint, this cluster suggests a balanced (and potentially utilitarian) use of their EVs. Most members of this cluster have moderate travel durations (15–60 min) and travel distances (2.5–10 km), and tend to spend under £ 10 per day on travel. This group also shows the highest proportion of multi-vehicle households and predominantly uses EVs for shopping and leisure purposes, highlighting their private, convenience-oriented mobility practices. Socio-demographically, as shown in Table 5, this group has a high proportion of individuals with Master's degrees, as well as a relatively even gender split and stable full-time employment. These characteristics might conventionally align with early adoption profiles in other shared mobility sectors (Guo and Zhang, 2021; Kim et al., 2015). However, unlike what's suggested in past studies, this group expresses limited enthusiasm for CSS.

As such, this discrepancy invites deeper interpretation. One possible explanation lies in domain-specific risk aversion. One possible explanation is that, unlike car-sharing or ride-hailing services, the CSS model requires opening up access to one's personal property. Such access may involve higher perceived risks or perceived lack of control. In this vein, studies have found that higher education levels can correlate with greater privacy and safety concerns in home-based sharing models, such as Airbnb (Gu et al., 2021; Xingjun et al., 2024). Given the socio-demographic profile of this cluster, these concerns may be especially salient, where the charger is physically connected to the host's property and electrical infrastructure.

Cluster 3 Economic-Centred (47.4% of the sample): This cluster constitutes nearly half the sample and displays a clear behavioural and motivational profile: high economic motivation, moderate moral motivation and lower social motivation. These respondents are willing to participate in CSS, as suggested by their high intention to share, but primarily for pragmatic, financially driven reasons, rather than social engagement or value-based ideals.

This cluster is featured with relatively mobile, urban, and not yet embedded in long-term property ownership. Members of this group are more likely to report daily travel durations of 30–60 min and travel distances of 2.5–5 km, with most spending £ 3–£ 10 on travel per day. Their EVs are predominantly used for leisure activities, and they show the highest proportion of flat dwellers and privately rented accommodations. However, this study lacks detailed data in how these residence features shape specific motivations and concerns - future studies could explore how dwelling type and homeownership status shape sharing motivations and potentially concerns.

Interestingly, despite this cluster being predominantly characterised by households with only one vehicle, 82.2% of these vehicles are EVs. Socio-demographically, this cluster is the youngest (mean age 34.7) and includes the highest proportion of students and part-time workers. Their financial situation appears more constrained compared to other clusters, which helps explain their elevated sensitivity to economic incentives and relative indifference to communal or environmental rationales. These findings echo prior literature, highlighting the economic dimension as a key enabler in early-stage participation in peer-to-peer sharing models (Böcker and Meelen, 2017; Hamari et al., 2016). However, the fact that their social and moral motivation scores lag behind suggests their perceived engagement with CSS may be transactional rather than transformative. In other words, their participation may be motivated primarily by personal benefit rather than broader values or community orientation. From a policy perspective, interventions such as tariff discounts and government-backed financial incentives, could be relatively more effective for these individuals. Notably, over-reliance on financial incentives should be monitored and prevented, which may erode long-term participation if not accompanied by added-value features (Zeiske et al., 2021).

Cluster 4 Highly motivated (18% of the sample): This segment stands out for its uniformly high scores across all motivational dimensions and intention to share chargers among all clusters. The profile suggests a group that not only sees personal benefit but also CSS as a socially valuable and morally desirable act.

Members of this cluster are heavy EV users, with the highest share of individuals reporting daily travel over 60 min and spending more than £ 10 per day on transport. In contrast to the "Economic-Centred" cluster, they are slightly more likely to live in owner-occupied homes, this indicates a balance of stability and openness and capability to participate in resource sharing.

This cluster shows the highest proportion of respondents using their EVs for business purposes, which maybe another reason that people in this cluster tend to me more open to CSS – previous research suggests that familiarity with sharing economy activities can enhance trust in sharing platforms and increase behavioural intention (Mittendorf, 2018; Hwang and Griffiths, 2017). Specifically, experience in other types of sharing economy activities (e.g., driving for Uber) enhance their familiarity and trust to CSS, which enhance their intention to participate in CSS (Pellegrini et al., 2023; Chakraborty et al., 2019). Furthermore, the motivational pattern in this cluster reflect a multi-layered orientation toward CSS, where financial benefit, communal participation, and ethical alignment reinforce one another. This stands in contrast to the "Economic-Centred" group, which is more narrowly driven by instrumental benefit. The "Highly Motivated" segment may therefore be more resilient to changes in financial incentives or platform design, as their intention is underpinned by broader psychological alignment.

Consequently from an implementation perspective, this group represents a high-priority target for early adoption, as they are both willing and able to participate. Interventions could focus on reinforcing their sense of contribution. For example, by highlighting the environmental benefits of hosting to enhance the social norm of sharing. Given their strong moral and social motivations, messaging strategies that go beyond financial appeals may prove particularly effective.

4.3. Cross-cluster insights

The four identified clusters reveal distinct motivational compositions and behavioural patterns, underscoring the heterogeneity of potential CSS hosts in the UK context. While each group is internally coherent, several cross-cutting themes and unexpected findings emerge that carry theoretical and practical implications. Broadly, compared to typical profiles reported in sharing economy studies – often characterised by younger, urban, and cost-conscious users (e.g., Böcker and Meelen, 2017; Hamari et al., 2016) – our segments show both overlap and divergence. On the one hand, while the" Economic-Centred" group broadly aligns with this pragmatic sharer profile, exhibiting high price sensitivity and flexibility, the "Highly Motivated" cluster reflects a more altruistic and environmentally engaged segment, closer to what Sahoo et al. (2022) describe as value-oriented adopters. On the other hand, the "Indifferent" and "Unmotivated Reluctant" groups complicate the conventional wisdom that higher education or homeownership correlate positively with sharing participation, suggesting the presence of other psychological or situational barriers such as trust or privacy concerns.

Second, our results reinforce prior research by confirming that economic motivation is a primary driver of CSS participation across all clusters (Magno, 2021; Böcker and Meelen, 2017). However, our data also reveal that economic incentives alone are not always sufficient to ensure participation—particularly in clusters like the "Indifferent," where social and moral motivations are low. In such cases, the prospect of financial gain may encourage some willingness to participate, but is unlikely to produce strong engagement or sustained adoption on its own as suggested in past studies (Yi et al., 2020).

5. Industrial and policy implications

The segmentation insights produced in this study offer practical implications for multiple stakeholders involved in the rollout of CSS, including policymakers, platform providers, and local authorities. As the adoption of electric vehicles (EVs) accelerates, pressure on public charging infrastructure will continue to grow, particularly in dense urban settings where installation capacity is limited. In this context, CSS offers a promising solution to expand access and improve network resilience. However, to scale effectively, CSS initiatives must recognise and respond to the motivational diversity among groups of charger owners.

The presence of a large “Economic-Centred” segment suggests that financial incentives remain a powerful enabler of participation. For this group, offering hosting bonuses, or one-time joining grants may be effective strategies to stimulate uptake. However, the findings also caution against relying solely on monetary incentives, especially in the longer term. If hosts perceive CSS as a purely transactional activity, their engagement may decline once the financial rewards plateau. In contrast, for the “Highly Motivated” group, who already exhibit a strong intention to participate, communication strategies could focus on highlighting the social and environmental benefits of CSS. For instance, platforms could provide impact metrics to strengthen hosts’ sense of contribution, such as the amount of CO_2 saved.

For less motivated groups, particularly the “Indifferent” and “Unmotivated Reluctant” clusters, the path to engagement may be more challenging. These potential hosts may require targeted outreach that addresses perceived barriers such as privacy concerns, or unfamiliarity with platform technologies. Here, interventions may need to go beyond messaging and include direct support mechanisms, such as simplified software interfaces, or pilot schemes. Given that these groups are also more likely to be higher in age, more established homeowners, strategies that emphasise trust and minimal disruption to routine may be particularly important.

Our findings should be interpreted in light of local parking infrastructure. The feasibility of CSS participation among hosts depends not only on willingness, but also on whether their home has a private driveway, garage, or accessible parking space where a charger can be safely shared. In London, such arrangements are unevenly distributed: detached and semi-detached homes are more likely to have driveways or garages suitable for hosting, while terraced houses and flats commonly lack dedicated parking (Li and Guo, 2014; Budnitz et al., 2024). This suggests that policy support may be needed to extend sharing opportunities to residents in denser or parking-constrained areas.

6. Conclusion

Amidst growing pressure on existing public charging infrastructure, this study explores the feasibility and host-side factors involved in expanding access through CSS. To this end, we conducted the first known segmentation study on hosts using LCA and survey data collected in London. Our objective was to identify distinct owner segments and uncover the motivational, socio-demographic, and behavioural factors shaping their willingness to participate in CSS.

This study has three main findings. First, four distinct clusters were identified: "Indifferent," "Unmotivated reluctant," "Highly Motivated," and "Economic-Centred." The four identified clusters can be grouped by their likelihood to participate in CSS: the “Unmotivated Reluctant” and “Indifferent” clusters (together comprising 34.6% of the sample) are generally unlikely to share their EV chargers, while the “Economic-Centred” and “Highly Motivated” clusters (accounting for 65.4%) show greater willingness to participate, albeit driven by different motivations. This result underscores the heterogeneity in hosts’ willingness to participate in CSS, highlighting the need for tailored strategies to encourage adoption of CSS as hosts. Second, economic motivation stands out as a crucial driver for CSS participation, particularly among groups labelled as ’Highly Motivated’ and ’Economic-Centred.’ For instance, younger respondents with limited financial flexibility show a strong inclination to participate, motivated by the prospect of earning income as charger hosts—where others, acting as chargees, pay to use their chargers. In contrast, higher aged and wealthier groups display notable reluctance, as the lack of economic incentive lessens their interest in CSS participation. This contrast underscores how financial need significantly influences openness to collaborative mobility-sharing models. Third, while some influencing factors align with those found in general shared mobility studies, this research identifies factors exclusive to CSS. Counterintuitively, a large proportion of respondents with higher education levels are in the groups that are less likely to participate in CSS. This contrasts with findings in other shared mobility sectors, where higher education typically correlates positively with adoption, such as in e-scooter use (Guo and Zhang, 2021), ridesharing (Efthymiou et al., 2013), and car-sharing services (Kim et al., 2015). Another finding that diverges from other shared mobility studies (Mouratidis, 2022; Codagnone et al., 2016) is that unemployed individuals (those who are not currently in paid employment) are more reluctant to participate in CSS. These findings underscore the importance of leveraging segmentation to capture CSS-exclusive enablers and barriers for different individuals, thereby coming up with targeted intervention or communication strategies.

This study makes several key contributions. First, to the best of our knowledge, this study is the first attempt to explore the factors influencing CSS uptake in the host side, thereby deepening our understanding of the key enablers and barriers for promoting transition to CSS for current private EV charger owners. We recommend that CSS companies prioritise financial incentives—such as reduced tariffs, subsidies, or tax relief—to encourage uptake, given the pivotal role of economic factors. Achieving this will require joint collaboration among multiple stakeholders, particularly the Greater London Authority, local councils, Transport for London, and grid companies. Second, there is no one-size-fits-all approach to promoting the uptake of CSS. Although intention toward CSS adoption were generally positive, the Economic-Centred and Highly Motivated clusters emerged as the most likely individual to participate, they were driven by different incentives. For instance, financial incentives such as hosting bonuses or lower electricity rates may resonate more with the Economic-Centred cluster, who are primarily driven by personal benefit. In contrast, the Highly Motivated group is also responsive to non-financial incentives such as community recognition and environmental framing, reflecting their broader values alignment. Third, this study provides an example of how a three-construct framework and clustering approach can be used to identify individuals with high likelihood of share as hosts. In practice, a similar procedure could be followed to support the rollout of CSS networks, complementing existing public EV infrastructure. This would result in a more connected and reliable charging network, ultimately accelerating the transition toward electric mobility.

Several limitations should be considered when interpreting these findings. First, due to the nascent concept and limited explorative research, the motivational factors included in this study was attracted from previous research to multiple contexts other than CSS, which may have overlooked the importance of other cultural and behavioural factors. In a similar vein, the perception of risks and concerns should be explored to add granularity in the factors that affect sharing intention as a host. Thus, we advocate qualitative research to be conducted to identify the range of factors that may affect adoption of CSS.

Second, as a trade-off for maintaining theoretical parsimony and modelling stability, socio-demographic variables were treated as inactive covariates. While this enabled the emergence of motivationally distinct classes, it also means that demographic associations are descriptive and should not be interpreted as drivers of segmentation. Future work could test whether alternative class structures emerge when demographic variables are included in class formation, we also advocate attempts that employ modelling approaches such as structural equation modelling (SEM) to explore causal pathways and quantify the statistical relationships between motivations and behavioural intention.

Third, while care was taken to provide a clear and neutral definition of CSS in the survey instrument, this introductory message was not pre-tested as part of a formal framing study. As such, we cannot fully rule out the possibility that the specific wording influenced participants' initial perceptions of CSS. Future research could benefit from exploring how different ways of presenting CSS (e.g., highlighting environmental, financial, or technological aspects) may affect acceptance or intention to participate.

In addition, while this study identified motivational drivers and user profiles, and have emphasized the importance of economic motivation, it did not empirically assess how, by utilizing such finding in the policy level, can add to uptake of CSS in the UK. Future work could employ choice modelling to examine how varying incentive levels influence charger sharing willingness.

Finally, while our model incorporated a range of socio-demographic variables, many of these (e.g., employment status, travel distance, tenure) were collected using single-item questions with limited granularity. As a result, our ability to interpret class-level differences based on these factors is constrained by the coarse categorization available. We advocate future research, particularly qualitative or mixed-methods work to explore these socio-demographic nuances in greater depth to contextualize these patterns.

CRediT authorship contribution statement

Yanghui Cao: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Yuerong Zhang:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was funded by the Royal Society Research Grant (RG/R1/251079).

Appendix. A. . Parameters of the estimated LCA-model with covariates

	Values	C.1	C.2	C.3	C.4	Wald
Prediction of indicators (measurement model)						
Economic motivation		−1.79	−0.60	0.15	0.98	460.62*
Social motivation		−1.76	−0.60	0.11	1.12	367.37*
Moral motivation		−1.92	−0.80	0.20	1.22	830.19*
Intention to share as host		0.43	0.20	0.23	0.29	928.06*
Prediction of latent class membership (structural model)						
Daily travel duration	Less than 15 mins	0.24	0.16	0.12	0.14	17.40*
	15 −30 mins	0.55	0.46	0.48	0.50	107.02*
	30 −60 mins	0.14	0.34	0.35	0.32	51.55*
	More than 60 mins	0.07	0.04	0.05	0.05	5.24*
	Less than 2.5 km	0.24	0.16	0.12	0.14	17.40*
Daily travel distance	2.5 −5 km	0.55	0.46	0.48	0.50	107.02*
	5 −10 km	0.14	0.34	0.35	0.32	51.55*
	More than 10 km	0.07	0.04	0.05	0.05	5.24*
Daily travel costs	Less than £ 3	0.59	0.37	0.26	0.25	35.89*
	£ 3 −10	0.28	0.53	0.63	0.67	221.03*
	More than £ 10	0.14	0.10	0.11	0.08	9.81*
Number of vehicles owned at household	None	0.00	0.01	0.01	0.00	4.91*
	One	0.72	0.66	0.68	0.71	262.2*8
	Two to three	0.28	0.32	0.30	0.28	41.40*
	More than three	0.00	0.02	0.01	0.02	2.04
EV ownership	Owner	0.83	0.78	0.82	0.75	331.02*
	Use someone else's EV	0.03	0.14	0.12	0.13	16.06*
	Rental	0.10	0.06	0.05	0.10	12.24*
	Others	0.03	0.01	0.01	0.02	2.04
EV trip purposes	Shopping	0.21	0.39	0.33	0.37	63.19*
	Leisure	0.24	0.13	0.12	0.15	18.75*
	Commuting	0.45	0.43	0.48	0.37	63.19*
	Business	0.03	0.05	0.05	0.11	13.48*
	Others	0.07	0.00	0.01	0.01	1.01

*significant at the 5% level

Data availability

The data that has been used is confidential.

References

Alonso-González, M.J., Hoogendoorn-Lanser, S., van Oort, N., Cats, O., Hoogendoorn, S., 2020. Drivers and barriers in adopting mobility as a service (MaaS)–a latent class cluster analysis of attitudes. Transp. Res. Part A Policy Pract. 132, 378–401.

Azarova, V., Cohen, J.J., Kollmann, A., Reichl, J., 2020. The potential for community financed electric vehicle charging infrastructure. Transp. Res. Part D Transp. Environ. 88, 102541.

Bak, A., Nawrocka, E., Jaremen, D.E., 2022. Sustainability" as a motive for Choosing Shared-Mobility Services: The Case of Polish Consumers of Uber Services. Sustainability 14 (10), 6352.

Böcker, L., Meelen, T., 2017. Sharing for people, planet or profit? analysing motivations for intended sharing economy participation. Environ. Innov. Soc. Transit. 23, 28–39.

Botsman, R., Rogers, R., 2010. What's mine is yours. rise Collab. Consum. 1.

Brown, T.A., 2015. Confirmatory factor analysis for applied research. Guilford publications,.

Brown, T.A., Moore, M.T., 2012. Confirmatory factor analysis. Handb. Struct. Equ. Model. 361, 379.

Bucher, E., Fieseler, C., Lutz, C., 2016. What's mine is yours (for a nominal fee)–Exploring the spectrum of utilitarian to altruistic motives for Internet-mediated sharing. Comput. Hum. Behav. 62, 316–326.

Budnitz, H., Meelen, T., Schwanen, T., 2024. Public residential charging of electric vehicles: an exploration of UK user preferences. Eur. Transp. Stud. 1, 100004.

Cao, Y., Zhang, Y., Cao, M., 2025. Exploring the influence of socio-demographic characteristics on the intention to share private electric vehicle chargers. Travel Behaviour and Society 41, 101084.

Chahine, R., Christ, S.L., Gkritza, K., 2024. A latent class analysis of public perceptions about shared mobility barriers and benefits. Transp. Res. Interdiscip. Perspect. 25, 101132.

Chakraborty, D., Bunch, D.S., Lee, J.H., Tal, G., 2019. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. Transp. Res. Part D Transp. Environ. 76, 255–272.

Charly, A., Thomas, N.J., Foley, A., Caulfield, B., 2023. Identifying optimal locations for community electric vehicle charging. Sustain. Cities Soc. 94, 104573.

Chen, J., Li, F., Yang, R., Ma, D., 2020. Impacts of increasing private charging piles on electric vehicles' charging profiles: a case study in hefei city, China. Energies 13 (17), 4387.

Cherry, C.E., Pidgeon, N.F., 2018. Is sharing the solution? Exploring public acceptability of the sharing economy. J. Clean. Prod. 195, 939–948.

Co-Charger., 2024. FAQs – Co-Charger. Available at: https://co-charger.com/faq/ (Accessed: 29 May 2025).

Codagnone, C., Abadie, F., Biagi, F., 2016. The future of work in the 'sharing economy'. Market efficiency and equitable opportunities or unfair precarisation? Inst. Prospect. Technol. Stud. Sci. Policy Rep. Jt. Res. Cent.

Department for Transport (DfT), 2022. UK Government's Electric Vehicle Infrastructure Strategy and Funding Plan. Available at: https://www.gov.uk/government/publications/government-electric-vehicle-infrastructure-strategy.

Dixon, J., Andersen, P.B., Bell, K., Træholt, C., 2020. On the ease of being Green: an investigation of the inconvenience of electric vehicle charging. Appl. Energy 258, 114090.

Efthymiou, D., Antoniou, C., Waddell, P., 2013. Factors affecting the adoption of vehicle sharing systems by young drivers. Transp. Policy 29, 64–73.

Elnadi, M., Gheith, M.H., 2022. What makes consumers reuse ride-hailing services? An investigation of Egyptian consumers' attitudes towards ride-hailing apps. Travel Behav. Soc. 29, 78–94.

Essus, Y., Rachunok, B., 2024. Electric vehicles limit equitable access to essential services during blackouts. npj Sustain. Mobil. Transp. 1 (1), 9.

Falchetta, G., Noussan, M., 2021. Electric vehicle charging network in Europe: an accessibility and deployment trends analysis. Transp. Res. Part D Transp. Environ. 94, 102813.

Frenken, K., Schor, J., 2019. Putting the sharing economy into perspective. In A research agenda for sustainable consumption governance. Edward Elgar Publishing,, pp. 121–135.

Greene, D.L., Kontou, E., Borlaug, B., Brooker, A., Muratori, M., 2020. Public charging infrastructure for plug-in electric vehicles: what is it worth?. Transp. Res. Part D Transp. Environ. 78, 102182.

Gong, D., Tang, M., Buchmeister, B. and Zhang, H., 2019. Solving location problem for electric vehicle charging stations-A sharing charging model. IEEE access, 7, pp.138391 - 138402.

Gu, H., Zhang, T., Lu, C., Song, X., 2021. Assesing trust and risk perception in the sharing economy: An empirical sutdy. Journal of Management Studies 58 (4), 1002–1032.

Guo, Y., Zhang, Y., 2021. Understanding factors influencing shared e-scooter usage and its impact on auto mode substitution. Transp. Res. Part D Transp. Environ. 99, 102991.

Hamari, J., Sjöklint, M., Ukkonen, A., 2016. The sharing economy: why people participate in collaborative consumption. J. Assoc. Inf. Sci. Technol. 67 (9), 2047–2059.

Hopkins, E., Potoglou, D., Orford, S., Cipcigan, L., 2023. Can the equitable roll out of electric vehicle charging infrastructure be achieved?. Renew. Sustain. Energy Rev. 182, 113398.

Hu, X., Yang, Z., Sun, J., Zhang, Y., 2021. Sharing economy of electric vehicle private charge posts. Transp. Res. Part B Methodol. 152, 258–275.

Hwang, J., Griffiths, M.A., 2017. Share more, drive less: millennials value perception and behavioral intent in using collaborative consumption services. J. Consum. Mark. 34 (2), 132–146.

International Energy Agency (IEA), 2023b. Global EV Outlook 2023. Available at: https://www.iea.org/reports/global-ev-outlook-2023.

International Energy Agency (IEA), 2023a. CO2 Emissions in 2023. Available at: https://www.iea.org/reports/co2-emissions-in-2023.

Joosup. 2025. Joosup: Share or rent EV chargers anywhere. Available at: https://www.joosup.com [Accessed 31 May 2025].

Kaushal, L.A., Prashar, A., 2022. Determinants of service consumer's attitudes and behavioural intentions towards sharing economy for sustainable consumption: an emerging market perspective. J. Glob. Inf. Technol. Manag. 25 (2), 137–158.

Kim, D., Ko, J., Park, Y., 2015. Factors affecting electric vehicle sharing program participants' attitudes about car ownership and program participation. Transp. Res. Part D Transp. Environ. 36, 96–106.

Lamberton, C.P., Rose, R.L., 2012. When is ours better than mine? a framework for understanding and altering participation in commercial sharing systems. J. Mark. 76 (4), 109–125.

LaMonaca, S., Ryan, L., 2022. The state of play in electric vehicle charging services–a review of infrastructure provision, players, and policies. Renew. Sustain. Energy Rev. 154, 111733.

Leismann, K., Schmitt, M., Rohn, H., Baedeker, C., 2013. Collaborative consumption: towards a resource-saving consumption culture. Resources 2 (3), 184–203.

Li, F., Guo, Z., 2014. Do parking standards matter? evaluating the London parking reform with a matched-pair approach. Transp. Res. Part A Policy Pract. 67, 352–365.

Magno, F., 2021. Utilitarian and altruistic motivations in using car sharing: the moderating role of perceived power. J. Clean. Prod. 317, 128409.

Marsh, H.W., Balla, J.R., McDonald, R.P., 1988. Goodness-of-fit indexes in confirmatory factor analysis: the effect of sample size. Psychol. Bull. 103 (3), 391.

Matzner, M., Plenter, F., Bezing, J.H., Chasin, F., von Hoffen, M., Lochte, M., Putz, S., Becker, J., 2018. Crowdstrom: Analysis, design, and implementation of processes for a peer-to-peer service for electric vehicle charging. In: Business Process Management Cases: Digital Innovation and Business Transformation in Practice. Springer International Publishing, Cham, pp. 337–359.

Mittendorf, C., 2018. Collaborative consumption: the role of familiarity and trust among millennials. J. Consum. Mark. 35 (4), 377–391.

Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: a latent class cluster analysis of Dutch travelers. Transp. Res. Part A Policy Pract. 83, 14–29.

Mouratidis, K., 2022. Bike-sharing, car-sharing, e-scooters, and uber: who are the shared mobility users and where do they live? Sustain. Cities Soc. 86, 104161.

Muchlisin, M., Soza-Parra, J., Susilo, Y.O., Ettema, D., 2024. Unraveling the travel patterns of ride-hailing users: a latent class cluster analysis across income groups in yogyakarta, Indonesia. Travel Behav. Soc. 37, 100836.

Muthén, B., Muthén, L.K., 2000. Integrating person-centered and variable-centered analyses: growth mixture modeling with latent trajectory classes. Alcohol. Clin. Exp. Res. 24 (6), 882–891.

Muthén, B.O., 2002. Beyond SEM: general latent variable modeling. Behaviormetrika 29 (1), 81–117.

Pellegrini, A., Borriello, A., Rose, J.M., 2023. Assessing the willingness of Australian households for adopting home charging stations for electric vehicles. Transp. Res. Part C Emerg. Technol. 148, 104034.

Plenter, F., Chasin, F., von Hoffen, M., Betzing, J.H., Matzner, M., Becker, J., 2018. Assessment of peer-provider potentials to share private electric vehicle charging stations. Transp. Res. Part D Transp. Environ. 64, 178–191.

Raman, G., Raman, G., Peng, J.C.H., 2022. Resilience of urban public electric vehicle charging infrastructure to flooding. Nat. Commun. 13 (1), 3213.

Sahoo, D., Harichandan, S., Kar, S.K., Sreejesh, S., 2022. An empirical study on consumer motives and attitude towards adoption of electric vehicles in India: policy implications for stakeholders. Energy Policy 165, 112941.

Skrondal, A., Rabe-Hesketh, S., 2004. Generalized latent variable modeling: multilevel, longitudinal, and structural equation models. Chapman and Hall/CRC,.

Tussyadiah, I.P., 2015. An exploratory study on drivers and deterrents of collaborative consumption in travel. In Information and Communication Technologies in Tourism 2015: Proceedings of the International Conference in Lugano, Switzerland, February 3-6, 2015. Springer International Publishing,, pp. 817–830.

Tussyadiah, I.P., Pesonen, J., 2016. Impacts of peer-to-peer accommodation use on travel patterns. J. Travel Res. 55 (8), 1022–1040.

van't Veer, R., Annema, J.A., Araghi, Y., de Almeida Correia, G.H., van Wee, B., 2023. Mobility-as-a-Service (MaaS): a latent class cluster analysis to identify Dutch vehicle owners' use intention. Transp. Res. Part A Policy Pract. 169, 103608.

Velkovski, B., Gjorgievski, V.Z., Markovski, B., Cundeva, S., Markovska, N., 2024. A framework for shared EV charging in residential renewable energy communities. Renew. Energy 231, 120897.

Vermunt, J.K., 2002. Latent class cluster analysis. Applied latent class analysis. Cambridge UniversityPress,.

Wang, Y., Shen, Q., 2024. A latent class analysis to understand riders' adoption of on-demand mobility services as a complement to transit. Transportation 51 (3), 1043–1061.

Xingjun, H., Mao, Z., Lin, Y., Shi, Q., Liu, F., Zhou, F., 2024. Sharing or privacy for private electric vehicle charging piles? Evidence from chongqing. Technol. Forecast. Soc. Change 203, 123350.

Yang, X., Liu, J., Zhuge, C., Wong, A.T.C., Wang, P., 2024. Exploring the potential of sharing private charging posts: a data-driven micro-simulation approach. Sustain. Cities Soc. 100, 105053.

Yi, J., Yuan, G., Yoo, C., 2020. The effect of the perceived risk on the adoption of the sharing economy in the tourism industry: the case of airbnb. Inf. Process. Manag. 57 (1), 102108.

Zeiske, N., van der Werff, E., Steg, L., 2021. The effects of a financial incentive on motives and intentions to commute to work with public transport in the short and long term. J. Environ. Psychol. 78, 101718.

Zervas, G., Proserpio, D., Byers, J.W., 2017. The rise of the sharing economy: estimating the impact of airbnb on the hotel industry. J. Mark. Res. 54 (5), 687–705.

Zhang, Y., Kamargianni, M., 2023. A review on the factors influencing the adoption of new mobility technologies and services: autonomous vehicle, drone, micromobility and mobility as a service. Transp. Rev. 43 (3), 407–429.

Zhang, Y., Kamargianni, M., Cheng, L., De Vos, J., Cao, M., 2024. Evaluating the accessibility of on-street household electric vehicle charging stations in London:

policy insights from equity analysis across emission zones. Energy Policy 195, 114375.