Investigating the adaptability of shared electric mobility system and their impacts on travel behaviour patterns

by

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Declaration

This thesis is submitted to University of Niccolò Cusano for the degree of Doctor of Philosophy (XXXVII Ciclo – Dottorato in Territorio Innovazione e Sostenibilità). I declare that this thesis and the original work presented in it is my own and has generated by me. The material presented has never been submitted to any other educational establishment for the purpose of obtaining a higher degree.

February 2025 Janak PARMAR

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Summary

Introduction and Motivation

The thesis explores how shared electric mobility systems (SEMS) – including stationed based shared e-cars, e-bikes, and e-scooters – can transform urban transport toward sustainability by reducing private car dependency, mitigating congestion, and lowering emissions. Despite their potential, SEMS adoption remains limited because of a complex mix of technical, infrastructural, behavioural, and policy barriers. In rapidly urbanising cities, where environmental degradation and inefficient land use are pressing concerns, the study emphasises the need to understand the multifaceted dynamics that underlie travellers' mode-choice behaviour as well as user willingness to pay for time savings. This summary encapsulates the comprehensive methodological approach, key empirical results, and policy recommendations presented in the thesis, offering critical insights for transforming urban mobility through shared electric mobility systems.

Methodological framework

The thesis structured into three interrelated parts:

1. **Fuzzy Multi-criteria Decision Making (MCDM) analysis:** Using a two-phase approach that combines the fuzzy Best-Worst Method (BWM) and the fuzzy Combined Compromise Solution (CoCoSo), the research identifies and ranks key barriers and evaluates policy-level solutions. Barriers are grouped into categories including behavioural issues (e.g., habitual use of private vehicles and negative perceptions), policy and governance challenges (e.g., lack of coherent strategic visions and investment), infrastructural shortcomings, technical limitations, and external factors. The fuzzy approach captures uncertainty in expert judgments and yields global ranking scores that point to the critical areas needing intervention. In addition, a sensitivity analysis confirms the robustness of the rankings against changes in category weights and model parameters.
2. **Structural Equation Modelling (SEM) for adoption intentions:** Integrating elements from the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), this empirical study investigates the psychological drivers behind SEMS adoption. Key latent constructs—personal innovativeness, environmental awareness, social influence, perceived usefulness, perceived risk, scepticism, and habit—are measured through survey data collected from commuters. The SEM results indicate that while factors such as personal innovativeness, perceived usefulness, and social influence positively contribute to adoption intentions, habit and scepticism (often stemming from strong car-usage patterns) are significant deterrents. Mediation and moderation analyses further reveal that the habit of using private vehicles reinforces both scepticism and risk perceptions, while sociodemographic factors (such as gender and education) also shape these relationships.

3. **Hybrid Latent-Class Latent-Variable (LCLV) choice model:** To capture heterogeneity among travelers, the third part segments the sample using a latent-class approach integrated with latent-variable modeling. Two distinct user classes emerge. The first segment—characterized by younger, non-habitual, moderate-income, and lower car-ownership individuals—tends to favor micro-mobility options like shared e-bikes and e-scooters. In contrast, the second segment consists of older, higher-income, habitual car users who show a stronger preference for shared e-cars. Additionally, willingness-to-pay (WTP) analyses estimate the monetary value travellers assign to saving time in various trip components (in-vehicle, access, egress, and waiting times). While many estimates are robust with narrow confidence intervals, other time components (particularly for certain SEMS modes) show wider uncertainty, indicating heterogeneity in respondents' time valuations.

Key findings and Mode substitution

The combined modelling effort yields several insights:

- **Barriers:** Behavioural inertia – expressed as the habitual use of private vehicles – is the most influential barrier, along with perceived high costs and insufficient awareness of SEMS benefits. Policy and infrastructural deficiencies further compound the challenge.
- **Effective solutions:** Solutions such as strategic financial investment strategies, improved charging infrastructure, optimal SEMS station locations, provisions toward transit-oriented development, and public awareness campaigns can contribute to widespread adoption of SEMS.
- **Adoption drivers:** Personal innovativeness and perceived usefulness are strong positive determinants of SEMS adoption. Social influence and environmental awareness play supportive roles, whereas perceived risk and scepticism (often driven by entrenched habits) have significant negative effects.
- **Heterogenous segments:** The latent-class analysis distinguishes two groups. Non-habitual commuters are more receptive to micro-mobility offerings, whereas habitual car users prefer solutions that closely mimic the convenience of private cars (e.g., shared e-cars). Simulated mode substitution patterns demonstrate that SEMS can effectively divert trips from private car use; however, an unintended shift from public transport is also observed, underscoring the need for careful integration.
- **Willingness-to-pay:** The WTP estimates for time savings vary by mode and trip component. For example, in one segment non-habitual users assign higher WTP values for reducing in-vehicle time in shared e-cars and are willing to pay more for reducing access/egress times in micro-mobility modes.

Policy implications and Conclusions

Based on these findings, the thesis recommends a comprehensive and multi-pronged approach for increasing SEMS adoption:

- **Infrastructure investments:** Develop a dense network of SEMS stations with dedicated charging and protected lanes to ensure high availability and reliability.
- **Economic incentives:** Initiate subsidies, reduced pricing, and temporary promotions that lower initial barriers for users and stimulate habit change.
- **Regulatory and coordinated frameworks:** Formulate coherent policies that establish clear operational guidelines, improve interoperability with public transport, and restrict private car parking in congested urban centres.
- **Public awareness and equity initiatives:** Launch targeted marketing campaigns to educate potential users about the environmental, economic, and convenience benefits of SEMS, with particular attention to underserved populations.
- **Integrated with public transit:** Create seamless multimodal networks through mobility hubs and integrated ticketing systems that minimize mode substitution away from sustainable public transport.

In conclusion, the thesis demonstrates that SEMS have the potential to reshape urban travel behaviour and contribute notably to sustainability goals. However, successfully transforming commuting patterns requires addressing not only technical and infrastructural challenges but also deeply rooted behavioural habits and policy shortcomings. Future research should extend these findings by incorporating revealed preference data, exploring inter-city and diverse socio-cultural contexts, and further examining the dynamic process of habit formation and disruption.

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Chapter 1

Introduction

1. Background

As global urbanization continues to accelerate, cities are facing mounting challenges in managing transportation systems that are efficient, sustainable, and equitable. The dominance of internal combustion engine (ICE) vehicles, particularly for passenger transport, has led to adverse environmental impacts, including air pollution, resource depletion, and climate change. The transport sector accounts for approximately 24% of global CO2 emissions, of which nearly 75% contribution comes from the passenger-based road transport[1]. It accounts for about 20% of EU's total emissions of CO2, and still on an unwanted growth trajectory[2]. In urban areas, the reliance on private vehicles further exacerbates these issues due to traffic congestion, leading to poor air quality and substantial economic costs to the society. For instance, the UK experienced an economic loss of £4.9 billion in 2019 due to traffic congestion[3] and expected to rise to £9.3 billion by 2030[4]. These trends highlight the urgency for transformative solutions in order to address urban mobility concerns.

Till date, public transport has been regarded as a sustainable travel alternative. However, it has its own challenges such as limited coverage, last-mile connectivity issues, lack of personalisation and flexibility (e.g., departure time scheduling), and peak-hour crowding (Jorge and Correia, 2013). The current transport market is fundamentally changing by delivering new opportunities for flexible, convenient, efficient, and responsive mobility solutions to deal with the sustainability challenges. Falling under the umbrella of smart mobility solutions, shared electric mobility offers promising pathway to direct urban transport towards sustainability (Becker et al., 2020; Shaheen et al., 1998). By combining the environmental benefits of electric vehicles with the flexibility and resource efficiency of shared mobility, it can reduce private

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[1] https://ourworldindata.org/co2-emissions-from-transport
[2] https://www.eea.europa.eu/publications/explaining-road-transport-emissions
[3] Press release from Transport for London
[4] Press release from INRIX

car dependency, alleviate traffic congestion, reduce parking demand, and improve air quality. These systems have the potential to support inclusivity by providing affordable travel alternatives for the individuals underserved by public transport and/or not capable to own private electric vehicles. Further, the micromobility solutions such as shared e-scooters and shared e-bikes can improve the catchment area of public transport by providing first/last-mile accessibility solutions (Baek et al., 2021; Shaheen and Chan, 2016). However, despite its substantial benefits, the adoption of shared electric vehicles remains subdue, with numerous barriers at different levels including behavioural, infrastructure, and policy domains. In-depth understanding of these barriers and factors driving shared electric mobility is of utmost importance for developing effective strategies to integrate these systems into current urban mobility networks.

Within the shared electric mobility ecosystem, three travel modes have been widely adopted across the globe – shared electric cars (also frequently termed as shared electric vehicles), shared electric bikes (or bicycles), and shared electric scooter, with two other options namely, shared electric mopeds and shared electric cargo-bikes[5] have been introduced in a few countries of Europe (e.g., Netherlands, UK, and Spain). Shared e-car system allows users to rent electric cars on a pay-as-you-go or subscription basis, eliminating ownership costs of private vehicle and providing a more sustainable alternative to private cars. These systems are deemed to be effective particularly in reducing car ownership and urban parking demand. For instance, studies in Germany and the Netherlands reveal that each shared car replaces 9–15 private vehicles (Kolleck, 2021; Oldenburger et al., 2019; Schreier et al., 2018). Additionally, it plays crucial role in facilitating long-distance urban commutes and enabling users to travel to/from areas with limited public transport coverage.

E-bike sharing services offer an efficient and environment-friendly mode of transport, particularly useful for short- to medium-distance trips. With large investments in bicycle infrastructure, shared bikes have gained more popularity across the globe. Further, their integration with public transport systems enhances accessibility to transit stations, especially when transit stations are not reachable by walking (Liu et al., 2023). These services can be regarded as an affordable means of transport for users (lower fare) as well as for operators (lower upfront costs compared to e-cars). It has more potential to curb traffic congestion and increase health benefits by promoting physical activity. According to study by (Zhang and Mi, 2018), bike sharing has led to reduction of 25,240 tons of CO_2 and 64 tons of NO_x emissions and 8358 tons of gasoline consumption. E-bike sharing has witnessed rapid expansion in European cities such as Paris, Barcelona, and Amsterdam, where cycling culture is deeply ingrained.

Another micromobility mode, e-scooter, has gained significant popularity due to its smaller size, convenience, and flexibility (Espinoza et al., 2019). They are widely adopted for first- and last-mile connectivity, particularly in densely populated areas. Besides, they can play important

[5] https://joyride.city/blog/shared-cargo-bikes-revolution/

role in improving accessibility and connectivity in lower density suburb areas where public transport connectivity is sparse and limited. E-scooters offer low-cost, low-emissions alternative to traditional transport modes, making them an integral component of the short-distance transport services. However, there are challenges related to safety, due to inadequate infrastructure leading to accidents. While cities like Copenhagen[6] and San Francisco[7] have implemented strict regulations to address safety and operational issues, the safety concerns remain one of the major challenges in most of the regions.

All these shared electric vehicle services can be categorised as either station-based (/docked) or free-floating (/dockless). Station-based services operate on a fixed network of stations located throughout the service area. Users can rent (or reserve online through app) a shared vehicle from one station and return it to another station within the same network. This service offers a predictable rental experience, as users can easily find a nearby station to rent and return a vehicle, which is generally useful for commuters who rely on shared vehicles for their daily commute. It is also easier for the operators to ensure the availability when and where users need them. It helps users as they do not have to search for parking place, reducing clutter on sidewalks and ensuring pedestrian convenience and safety. The disadvantages include limit coverage, particularly in sprawling cities/areas with lower density, and higher initial investments for service provider in terms of station infrastructure. In case of free-floating services, users do not require to find a station. Instead, they can find the serviceable shared modes within the designated service area through a smartphone app and unlock them using a code or QR scan. This gives free-floating services a higher coverage of network, making them more accessible. Moreover, users have freedom to start and end their rental according to their convenience, especially useful for one-way trips. They are cost-effective in terms of station infrastructure building compared to station-based counterpart. However, free-floating service require higher and unsustainable costs in terms of relocation of shared vehicles to avoid the demand-supply mismatches. Further, users' tendency to park these vehicles anywhere can lead to cluttered sidewalks, making it difficult for pedestrians to navigate and sometimes difficult even for operators to locate them. Since limited attention has been given to station-based electric vehicle sharing in the current literature, the consensus on attractiveness of these services could not be made. Therefore, this thesis focuses on the station-based services, by examining peoples' intentions to adopt them and heterogeneity in their decision-making process, thereby contributing to the already scarce knowledge on users' adoption of these system.

Several European countries including the Netherlands, Germany, France, Spain and UK have proposed the initial policy frameworks to promote the use of shared mobility services (e.g., SUMP[8], Future of Transport programme[9]). However, at this juncture, their impacts are limited to spark the upliftment of shared mobility adoption, specifically from current car-users (Chi et

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[6] Press release of Technical and Environmental Administration, Copenhagen (18/10/2021)
[7] https://www.sfmta.com/scooter-safety-campaign-2023
[8] https://transport.ec.europa.eu/transport-themes/urban-transport/urban-public-transport-shared-mobility
[9] https://www.gov.uk/government/collections/future-of-transport-programme

al., 2023). The city authorities currently have limited knowledge on how to efficiently organise the shared electric mobility systems. Moreover, its status within the current transportation system and applicability of most existing transport policies to this emerging mobility form is unclear at present (Aba and Esztergár-Kiss, 2023). For the development of successful policy frameworks, it is essential to involve stakeholders from multifaceted disciplines in the decision-making process. This can be inevitably advantageous to understand the mobility needs from the perspectives of users, mobility operators, planners, and policymakers, which may not only sustain the loyalty of current users but also attract the non-users to choose such services for their routine travel activities. To address this aspect, this thesis endeavours to understand and analyse the opinions of multiple stakeholders involved in delivering and regulating the shared electric mobility services.

2. Research gaps

There is abundant literature focusing multifaceted landscapes of shared electric mobility, including behavioural aspects such as adoption intentions of innovative transport modes and mode substitution (mostly through stated preference data), assessment of users satisfaction with already established shared mobility alternatives, analysing usage pattern using revealed spatiotemporal usage data, studying impacts of shared electric mobility, and choosing optimal locations for shared mobility stations amongst others. The significant factors from these studies can be pertaining to either users (e.g., attitudes), operators (e.g., charging facilities), and/or policymakers (e.g., effective implementation and regulation). While previous studies have focused only on some of these aspects, to the best of author's knowledge, none has investigated the trade-offs between them. This study addresses this gap through experts' opinion-based analysis using an integrated multi-criteria decision-making (MCDM) method.

Further, most studies primarily focus on technological and infrastructural factors, with less attention given to the psychological aspects. The past approaches largely neglect the prominent aspect of habitual travel behaviour, for example, repetitive nature of mode choice behaviour. Past research showed that the individuals with established travel routines, such as commuting mode choice, are less likely to consider unfamiliar alternatives, unless driven by strong motives (de Kruijf et al., 2018; Gardner, 2015; Gössling, 2020a). Hence, it is important to understand whether and to what extent a mode-use habit affects the process of mode choice decision. While it is expected that the introduction of shared electric mobility would substitute the private car trips, it is quite possible that it also may substitute the use of public transport and active modes. These dynamics may well depend upon the personal characteristics, attitudes, current vehicle ownership levels, state of public transport, and features of shared electric mobility modes. However, most of the recent studies focusing on shared electric mobility adoption through discrete choice analysis neglects the importance of including individuals' psychological attitudes such as values, attitudes, and perceptions. This thesis attempts to address these gaps by investigating the interaction of shared electric mobility modes with traditional transport modes such as private cars and public transport.

3. Research objectives and methods

To address the above-described research gaps, this thesis aims to contribute both in terms of methodology and policy-practice contextual to the shared electric mobility adoption. The specific objectives of this work are as follows:

1. Identifying the potential barriers to the adoption of shared electric mobility and policy-level solutions effectively overcome the barriers.
2. Employing a multi-criteria decision-making approach to evaluate and rank the barriers and policy-level solutions.
3. Investigating non-users' adoption intentions for shared electric mobility services through their psychological and socio-economic characteristics.
4. Understanding non-users' travel preferences for shared electric mobility services and their interaction with traditional transport modes through discrete choice analysis.
5. Incorporating mode-use habit to understand the discrete preference heterogeneity in choice behaviour.
6. Investigating the effects of personal attitudes on choice of various electric shared modes through integrated choice models.
7. Examining the substitution patterns induced by electric shared modes on traditional transport modes.

In order to achieve the above objectives, the thesis first starts with synthesizing a comprehensive list of potential barriers and policy-level solutions cited in extant literature. A Delphi-based risk analysis approach is then deployed for initial evaluation of these barriers and solutions. After finalising the sets of barriers and solutions, MCDM techniques – fuzzy best-worst method (BWM) for barriers and fuzzy combined compromise solution (CoCoSo) technique for solutions are applied to experts' opinion data. This gives an insight into the most critical barriers affecting shared electric mobility adoption and potential policy-level solutions to overcome these barriers. **Chapter 2** is dedicated to this analysis.

Chapter 3 delve into understanding individuals' adoption intentions for the station-based shared electric mobility services. A comprehensive structural equation modeling (SEM) framework is formulated for this purpose. In particular, an extended model that combines technology acceptance model (TAM) and theory of planner behaviour (TPB) is proposed. A latent construct of "Intentions to adopt (IA)" is modelled as a function of individuals' psychometric attitudes (representing their travel preferences), socioeconomic characteristics, vehicle ownership levels, and importantly, mode-use habit. Besides, a few significant mediating and moderating effects of these variables are demonstrated. Study findings suggest positive and negative associations of several latent constructs with IA, and significant negative influence of habit on IA. Habit of car-usage has positive impacts user' scepticism and perceived risk, and negative impact on perceived usefulness, underscoring the critical role of habit in shaping adoption behaviours. These results are useful for better understanding of the underlying psychological mechanisms influencing the adoption intentions.

Chapter 4 takes a different approach by extending the results chapter 3. This chapter investigates the adoption dynamics of shared electric mobility through stated preference data and individuals' psychological attitudes. It is rational to assume that the travel preferences and choice behaviour may not be homogeneous across the population, but a group of individuals may exhibit distinct preferences than others. This can be distinguished at broader level based on their personal characteristics. A novel latent-class latent-variable (LCLV) model is proposed for this purpose, which is a combination of latent class choice model (LCCM) and integrated choice and latent variable model (ICLV). In LCCM, latent class segmentation is modelled conditional upon the sociodemographic characteristics and mode-use habit, while class-specific ICLV models are estimated as a function of mode-specific attributes and several latent variables. To the best of author's knowledge, this is the first study taking comprehensive approach in context of shared electric mobility literature. Two latent classes are identified as habitual and non-habitual individuals with distinct associated sociodemographic variables. Furthermore, a substitution pattern is analysed to examine the current mode of travel from which modal-shift takes place. Lastly, several key policy interventions are discussed that provide valuable insights into the dynamics of shared electric mobility adoption and its potential impacts on urban transport systems. Studies in **Chapter 3** and **Chapter 4** relies on the same data focused on commute trips; collected from various cities in England.

Chapter 5 synthesises the conclusions made from different studies presented in the body of the thesis. It also outlines the possible future directions in similar research domain.

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Chapter 2

Barriers and solutions for adopting shared electric mobility: an integrated fuzzy-MCDM approach

Abstract

This chapter investigates the adoption of shared electric mobility system using an integrated two-phase multi-criteria decision-making approach. This study systematically identifies and ranks the key barriers and policy-level solutions essential to overcome barriers for wider adoption of shared electric mobility. Withing the MCDM framework, the fuzzy Best-Worst Method is employed to assess the weights of barriers and sub-barriers, while the fuzzy Combined Compromise Solution method, enhanced with Bonferroni mean operators, prioritizes policy solutions. Findings highlight behavioural barriers, such as the habitual use of private modes of transport and higher perceived costs, are the most significant, followed by policy and governance barriers such as lack of coherent SEMS policies and coordination between involved authorities, and infrastructural barriers such as accessibility to SEMS, suitability of current city infrastructure, and availability of land resources. Key solutions include strategic financial investments, improved charging infrastructure, optimal SEMS station location, transit-oriented development, and public awareness campaigns. The study underscores need for a coherent national framework and supportive policies, offering critical insights to promote shared electric mobility and sustainable urban transport. This research provides a comprehensive decision-support framework for policymakers, enabling them to prioritise policy interventions and allocate resources effectively. By simultaneously addressing multiple barriers and solutions trade-offs, the findings contribute to developing sustainable, efficient and user-centric shared mobility solutions.

Keywords: Consumer adoption; Barriers; Decision making; Fuzzy BWM; Fuzzy CoCoSo; Shared electric mobility; Sustainability

1. Introduction

As urbanization continues to accelerate globally, cities and regions are experiencing a sharp increase in trips made by internal combustion (IC) engine vehicles which is contributing to climate change, air pollution, and depleting natural resources. The UK Department for Transport (DfT) has forecasted that there will be an increase of up to 85% in the congestion levels by 2040 costing the UK economy a large sum of £307 billion between 2013 and 2030 (LGA, 2017). According to recent publications, transport sector is responsible for 27% of the UK domestic greenhouse gas (GHG) emissions, which is the highest across sectors (DfT, 2021). Such issues have led the global economies to plan towards restructuring the urban mobility systems as well as appropriate enforcement of policies. Technological developments and digitalization in recent times have facilitated governments and businesses to rethink and reshape the future transportation that can be smart and more environment friendly. Shared electric mobility services, encompassing e-scooter, e-bike, e-moped, and e-car sharing programs, have become widely recognised as one of the means of reaching a transition to low emission sustainable transportation systems. They allow users to access vehicles in a flexible manner without paying expensive fixed costs of ownership such as purchase, insurance, and maintenance. The users of shared schemes have to pay only day-to-day variable costs of hiring a vehicle at pay-as-you-go rates. Besides, they provide convenient and flexible travel options, including first- and last-mile trips. Since electric vehicles are typically well suited for urban areas and city surroundings, many local authorities are attempting to include shared electric mobility system in their transport systems (also often referred as shared electric mobility) in numerous ways by providing incentives and financial supports (Bakker and Trip, 2013).

At this juncture, it is important to understand the demand and adoption of such emerging services, which is critical in facilitating effective market penetration. The usage of shared electric mobility system (SEMS) has remained low, largely because of their limited potential at present (Bösehans, et al., 2023). Despite its benefits, receiving acceptance to SEMS from transport users has been a challenge with numerous barriers at various levels including behavioural, infrastructural, and political domains. The city authorities currently have limited knowledge on how to efficiently organise the SEMS system. Moreover, its status within the existing transportation system and applicability of existing rules to this emerging mobility form is unclear at present (Aba and Esztergár-Kiss, 2023). Therefore, it is crucial to determine the policy initiatives needed for improving service quality and efficiency which can stimulate the uptake of SEMS. Therefore, the aim of the research here is to investigate the possible barriers affecting the demand and user adoption of station-based SEMS and to distinguish the potential policy measures (termed as Solutions hereafter) to overcome these barriers.

The research questions of this study are:

1. Which are the critical barriers related to the use of station-based SEMS requiring due attention for necessary policy-level interventions?
2. Which policy implications could be the most effective in overcoming barriers and attracting users towards SEMS?

The extant literature has explored multifaceted landscape of the shared mobility system. This includes investigating behavioural aspects, adaptability of new mobility technologies and modal substitution (Aguilera-García et al., 2020; Blazanin et al., 2022; Bösehans et al., 2024; Bösehans et al., 2023; Curtale & Liao, 2023; Eccarius & Lu, 2020; Jie et al., 2021; Kavta et al., 2024; Kim et al., 2015; Liao et al., 2024; Luo et al., 2023; Noland, 2021; Reck et al., 2022; Zuniga-Garcia et al., 2022), assessing users satisfaction with the current shared mobility options (Cheng et al., 2024; Kim et al., 2015; Si et al., 2024; Xia et al., 2022), analysing usage pattern of current shared electric mobility systems (Bösehans et al., 2024; McKenzie, 2019; NACTO, 2019; PBOT, 2019; Romanillos et al., 2018; Sprei et al., 2019), studying impacts of shared electric mobility (de Bortoli and Christoforou, 2020; John et al., 2024; Kazemzadeh and Sprei, 2024; Roca-Puigròs et al., 2023; Trivedi et al., 2019), selecting optimal locations for EV-sharing stations (Fazio et al., 2021; Guler and Yomralioglu, 2021; Kabak et al., 2018; Lin et al., 2020; Nikiforiadis et al., 2021; Svichynska et al., 2023; Zou et al., 2021) among others. Previous literature reviews reveal key factors pertaining to either users, operators, or government authorities. From users' point of view, for instance, awareness about the EV sharing as well as sustainability, perception toward electric vehicles and shared mobility, private mode habits and social stigma, reliability of the vehicles and operators, accessibility of shared vehicles, safety, weather conditions, and availability of real-time data are among the important factors frequently cited in the literature. Likewise, factors such as, coordination with local authorities, availability and efficiency of charging infrastructure, availability of space, real time information system, and tariff plans and incentives are important from operators' perspective. From government's viewpoint, policymaking and regulations for wide adoption of the shared mobility, know-how for effective implementation of services, proper coordination with operators, understanding requirements of users as well as operators, initial investments for suitable infrastructure, marketing and awareness campaigns are the critical factors to consider for successful adoption of SEMS. Previous studies have focused on only some of these factors, however, none of them has investigated the trade-offs between them where the focus of this research lies. Albeit, from policy-making perspective, it is essential to understand beforehand how these factors (can also be characterised as barriers), taken together, influence the successful implementation, wider adoption, and effective operation of SEMS.

For the development of a successful policy framework, it is critical to involve stakeholders from multifaceted disciplines in the decision-making process. Specifically, the present study employs an integrated multi-criteria decision-making (MCDM) method that uses the experts' opinions to prioritize SEMS barriers and to rank the effectiveness of potential solutions in uplifting the SEMS usage, taking case of the United Kingdom. The study utilised a systematic Delphi-based survey initially to confirm the derived list of barriers and solutions. The Best-Worst method (BWM) (Rezaei, 2015) and recently introduced Combined Compromise Solution (CoCoSo) (Yazdani et al., 2019) technique was then adopted to evaluate the barriers and rank the solutions respectively. For assessing the ambiguity and uncertainty in decision makers judgements for qualitative evaluation, fuzzy set theory proposed by (Zadeh, 1965) was integrated with both the MCDM methods. The adopted methodological approach enables systematic and consistent evaluation of expert judgements regarding the relative importance of the barriers and solutions. Further, it provides a data-driven prioritisation of policy solutions, supporting decision-makers in allocating resources effectively.

In terms of contribution, this study systematically identifies and analyses the critical barriers that may hinder the widespread adoption of shared electric mobility systems. This is necessary in understanding the challenges that need to be overcome for the successful penetration in current urban transport systems. Further, the study provides valuable insights into the policy implications that will be effective when addressing these barriers. By uncovering the limitations of current systems at various levels, planners and policymakers can be in a better position to decide on most desirable policy interventions based on this study. While most extant studies apply MCDM framework to understand the optimal charging locations, vehicle sharing station locations, barriers in adoption of personal EVs, ours is the first study to identify the barriers and policy measures for widespread diffusion of SEMS to the best of our knowledge. The hybrid fuzzy MCDM model proposed in this study can be employed in any geographical context to get critical insights and to tailor relevant decision framework.

The rest of the chapter is structured as follows: Section 2 presents detailed methodology comprising identification of barriers and solutions, and mathematical framework of the proposed MCDM model. Section 3 describes the case study of SEMS adoption using experts' opinion data, results, and sensitivity analysis. Section 4 discusses the obtained results and recommendations for uplifting SEMS mode share. Section 5 presents the conclusions and some potential avenues for future research.

2. Method

This section presents the overall workflow of the study (see Figure 2.1). Initially, a list of barriers and solutions for SEMS adoption and a panel of experts was identified. After that, the survey was conducted in two-phases via email: a) first phase contained a systematic Delphi-based questionnaire to obtain expert's consensus on the selected list of barriers as well as solutions, b) second phase comprised the main MCDM-based survey based on the finalised list of barriers and solutions. Then, MCDM methods were employed to evaluate and estimate the weights of the barriers. Further, these weights were used in ranking the policy-level solutions to overcome the SEMS barriers. The proposed methodology is explained in detail in subsections.

2.1. Determining SEMS barriers and solutions

Firstly, an initial list of 37 sub-barriers and 23 solutions for SEMS adoption was formulated based on the literature review and authors' judgements. Since there are no previous studies specifically focusing on barriers in adoption of SEMS, the listed sub-barriers and solutions in this chapter were synthesised after studying multiple published articles, working papers, reports, and other online sources. The sub-barriers were classified into five categories namely, "Behavioural barriers", "Policy and governance barriers", "Infrastructural barriers", "Technical barrier", and "External barrier" based on their characteristics. Then, the experts were asked to give their opinion on each of these sub-barriers and solutions through the systematically framed Delphi survey. Experts were asked to evaluate each sub-barrier based on their expected probability (EP) of occurrence which denotes whether a particular barrier will occur to individuals' decision-making process when they consider travelling with SEMS (scaled on 0-100%), impact (I) of sub-barrier on individual's choice-making (5-point Likert scale), desirability (D) of considering a sub-barrier at strategic level of planning (5-point Likert scale). For solutions, similar questions were asked except EP. Readers can find more details at (Parmar et al., 2023a), where the related details and results of Delphi survey are discussed by the authors. After assessing the experts' opinions and survey results, a total of 30 sub-barriers and 20 solutions were finalised for the main MCDM-based survey. Table 2.1 and Table 2.2 present the details of the finalised barriers, sub-barriers and policy-level solutions.

Table 2.1 List of selected barriers and sub-barriers.

Barriers	Sub-barriers	Description
Behavioural barriers (B1)	B11	Little awareness about the SEMS technology and its benefits may lead to lack of confidence
	B12	Negative perception towards the SEMS
	B13	Habit of using private modes – stigma to not giving up the private-vehicle ownership or use (Due to personal or household circumstances)
	B14	Lack of sustainability awareness
	B15	Performance and Range anxiety among users
	B16	Higher perceived cost to the users – generally compared with public transport
Policy & Governance barriers (B2)	B21	Lack of future visions, priorities, and coherent & nationwide policy – limited growth prospects
	B22	Lack of marketing strategies to promote the use
	B23	Poor interventions with the local authorities and regulations
	B24	Lack of required capital investments for developments and operations
	B25	Difficulties in incentivizing users
	B26	Lack of proper coordination between involved authorities
	B27	Time based tariffs limit the use – multiple stops enroute incur higher costs
Infrastructural barriers (B3)	B31	Un(/less) suitable city infrastructure at current levels
	B32	Reliability of vehicles as well as operator support
	B33	Access to and availability of SEMS at origin
	B34	Access to and availability of SEMS at destination

	B35	Unavailability of required space – stations, charging points, separate lanes where needed)
	B36	Poor/Unsuitable physical conditions of roads and Road network (including terrain) – safety
	B37	Poor intersection/junction management – safety
	B38	More number of cross streets (more junctions) – increased travel time due to waiting
Technical barriers (B4)	B41	Lack of know-how for planning SEMS to governing authorities (may lead to poor implementation)
	B42	Uncertain availability – due to inefficient charging infrastructure and larger charging layovers – limits the supply
	B43	Poor integration with public transport systems – accessibility and fare system
	B44	Unavailability of real-time vehicle data – evaluation and improvement of system
	B45	Easiness of using service – IT based services
External barriers (B5)	B51	Less suitable according to the individuals' demographics
	B52	No fulfilments of trip requirements – higher trip length, greater travel time, multiple destinations enroute
	B53	Unfavourable weather conditions
	B54	Exposure to increasing levels of pollution in open vehicles hinders adaptability – health

Table 2.2 List of selected policy measures.

Solutions	Description
P1	Provisions for congestion pricing / road pricing strategies for private vehicles
P2	Establishment of parking restriction policies
P3	Creating awareness campaigns for sustainable transport amongst the citizens
P4	Making people aware of the benefits of using electric shared-vehicles – at individual and societal levels
P5	Perform initial assessments and benchmarks from the foreign (other successful) examples
P6	Prior assessment for the optimal locations for SEMS stations – access/egress to O&D, PT locations, mobility needs & demand
P7	Provision for High taxations for private vehicle ownership – include environment and CO2, NOx emission taxes
P8	Formulating transport pricing on the basis of the 'polluter-pays' and 'user pays' principles – to ensure fair treatment of PV users, shared users and PT users

P9	Improvements in charging infrastructure and its availability – to decrease the layover (The idle time between trips when it is required to charge the vehicles)
P10	Established policies towards transit-oriented development and 15-minutes city
P11	Development of financial strategies to implement quality network for micro-mobility routes and to eliminate missing links
P12	Develop tools & techniques to evaluate the services at frequent time intervals
P13	Improving digital accessibility to SEMS services (digital services perceivable, operable and understandable by all)
P14	Provisions for supportive local authorities and policies that can aid in effective operations
P15	Consideration of social equity while planning new infrastructure – to ensure the transport needs of communities irrespective of their social and economic characteristics
P16	Close coordination between local authorities and operators to better understand the market conditions and requirements and efficient operations
P17	Provisions should be in favour of the unified planning and control systems at authority level
P18	Provision of single fare policy within the multimodal transportation (comparatively lower fares can attract more users)
P19	Increased accessibility to low/medium income households
P20	Increased accessibility to the areas with mobility issues (not well served by PT)

2.2. Identifying panel of experts

In multi-criteria analysis methods, obtaining experts' opinion is a crucial aspect for the evaluation of criteria and sub-criteria, and determining the most appropriate alternatives/solutions. As such, it is essential to carefully assemble a balanced group of experts with diverse backgrounds, considering the nature and requirements of an MCDM study. Typically, number of experts engaged in MCDM survey revolves around five to fifteen individuals. (Feng et al., 2021) used evaluations from five experts to select optimal electric-vehicle charging station by employing integrated linguistic entropy weight (LEW) method and fuzzy axiomatic design (FAD). (Xue et al., 2024) engaged eight experts to evaluate the critical barriers to EV business model innovation using MCDM-based Failure Mode and Effect Analysis (FMEA) approach. (Tarei et al., 2021) utilised a panel of ten experts to investigate the barriers to the adoption of personal EVs in India market using BWM and Interpretive Structural Modeling (ISM). (Lahane and Kant, 2021) employed a panel of fifteen experts to assess circular supply chain enablers (CSCEs) and rank the performance outcomes using Pythagorean fuzzy analytic hierarchy process (PF-AHP) and PF-CoCoSo. because an excessive number of involvements could compromise the accuracy and reliability of the assessments.

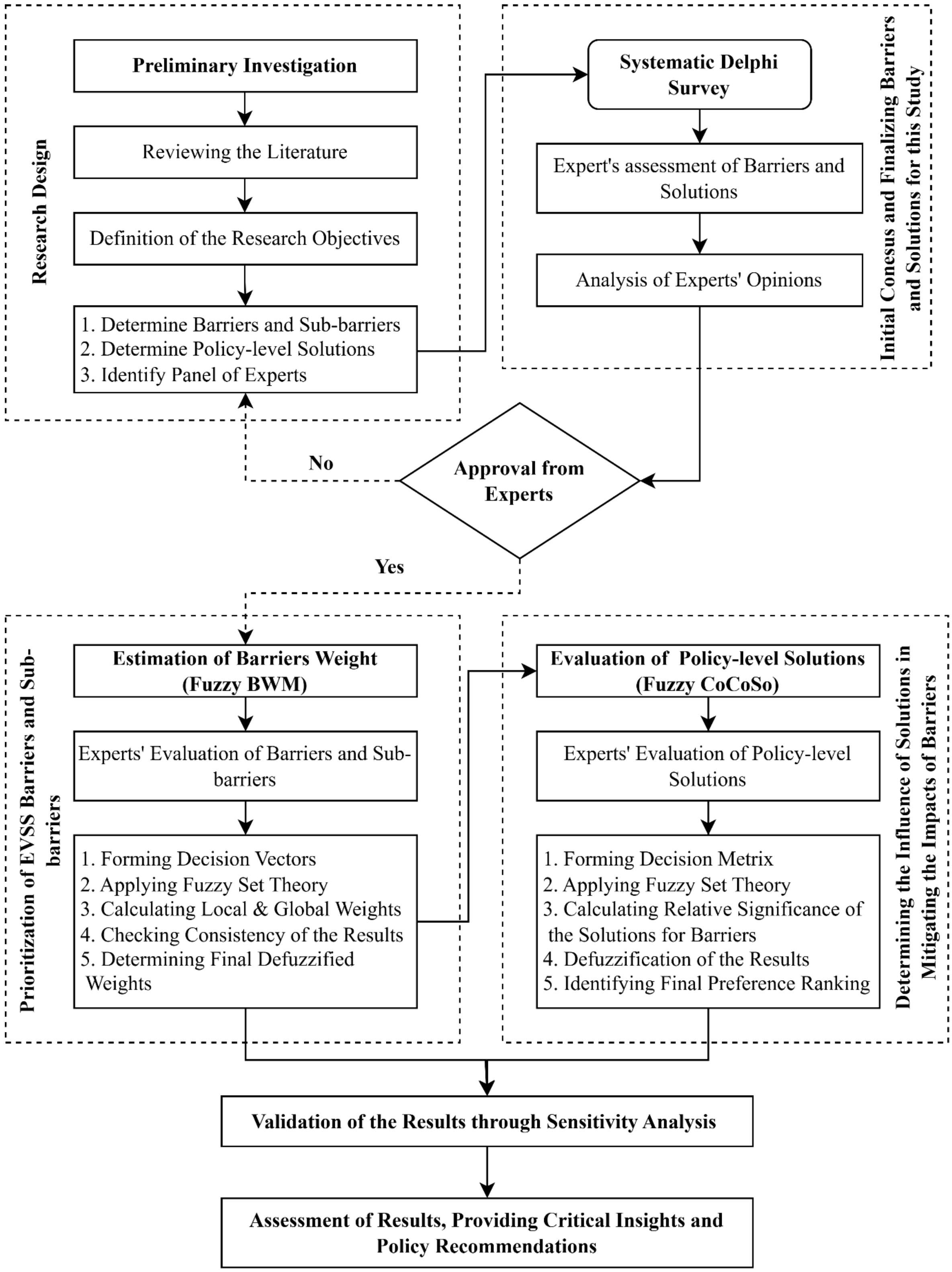

Figure 2.1 Workflow of the proposed study.

In this study, a panel of twelve experts was selected based on their associated expertise and active involvement/contribution relevant to the shared mobility, transport planning, and electric mobility policy. The experts were affiliated with academic institution (experts in transport research and mobility systems), public authorities (policy and decision-makers in transport planning), and the SEMS industry (i.e., operator/service provider). All the experts possessed substantial qualifications, knowledge, and experience within the scope of this study. Further details about the experts are available in Appendix A4.

2.3. MCDM framework

MCDM methodologies have been widely applied to determine rank of the alternatives (*solutions* here) based on the weights of numerous conflicting criteria (*barriers* here). In this study, BWM was utilised to estimate the weights of the barriers and sub-barriers and CoCoSo method to rank the solutions. Since human qualitative judgements are often associated with the ambiguity and uncertainty due to lack of sufficient information (possibly) about the criteria, it is more practical to apply fuzzy numbers rather than crisp values to compare subjective elements in MCDM problems (Bellman and Zadeh, 1970). This approach reflects more realistic situations and yields more convincing results. Further, since emerging mobility solutions like SEMS are still in their early stage in most regions, the subjective assessments are likely to be influenced by incomplete or uncertain information. Therefore, this study has incorporated trapezoidal fuzzy numbers with both the MCDM techniques to address the issues of uncertain decision making corresponding with the linguistic variables. The triangular fuzzy numbers (TFNs) and trapezoidal fuzzy numbers (TrFNs) are the two most used in literature while dealing with uncertainty in decision making. TFN is considered as a subset of TrFN when two most optimistic values are equal in TrFN. This study has adopted TrFN as they are more significant while developing a method, provide better solution in uncertain decision-making, and good enough to capture the vagueness of fuzzy evaluation (see Appendix A1 for basic details of TrFN). This section provides a brief overview of the methods used in this research.

2.3.1. Notations

The important notations used in this study are described as follows:

C : set of n decision criteria, $C = \{c_i \mid i = 1(1)n\}$, where c_i represents ith barrier/sub-barrier.

S : set of potential policy-level solutions, $S = \{s_j \mid j = 1(1)m\}$, where s_j represents jth solution.

$\tilde{V}_{Bi}$: fuzzy Best-to-Others vector $(\tilde{v}_{B1}, \tilde{v}_{B2}, ..., \tilde{v}_{Bn})$, where $\tilde{v}_{Bi}$ represents the fuzzy preference of the best criterion C_B over criterion i.

$\tilde{V}_{iW}$: fuzzy Others-to-Worst vector $(\tilde{v}_{1W}, \tilde{v}_{2W}, ..., \tilde{v}_{nW})$, where $\tilde{v}_{iW}$ represents the fuzzy preference of criterion i over the worst criterion C_W.

$\tilde{w}_i$: optimal trapezoidal fuzzy weight of criteria i, $\tilde{w}_i = (l_i^w, m_i^w, n_i^w, u_i^w)$.

$\tilde{\xi}$	:	objective function in fuzzy-BWM problem, $\tilde{\xi} = \left(l_{\tilde{\xi}},\, m_{\tilde{\xi}},\, n_{\tilde{\xi}},\, u_{\tilde{\xi}}\right)$.
$R\left(\tilde{w}_i\right)$	:	graded mean integration representation (GMIR), which provides defuzzified value of the fuzzy number.
X	:	initial decision matrix based on predefined linguistic terms, $X = \left[x_{ij}\right]_{m\times n}$, where x_{ij} represents the evaluation of solution *S* against criteria *C*.
$\tilde{X}$	:	the decision matrix represented by trapezoidal fuzzy numbers $[\tilde{X}]_{m\times n} = \left[\left(\tilde{x}_{ij}^{l},\, \tilde{x}_{ij}^{m},\, \tilde{x}_{ij}^{n},\, \tilde{x}_{ij}^{u}\right)\right]_{m\times n}$, where $\tilde{x}_{ij}$ is the fuzzy form of x_{ij}.
$\tilde{Z}$	:	normalized fuzzy decision matrix $[\tilde{Z}]_{m\times n} = \left[\left(\tilde{z}_{ij}^{l},\, \tilde{z}_{ij}^{m},\, \tilde{z}_{ij}^{n},\, \tilde{z}_{ij}^{u}\right)\right]_{m\times n}$.
$SB_i^{p,q}$	:	weighted sum of a solution i expressed using fuzzy normalized weighted Bonferroni mean (NWBM) in fuzzy-CoCoSo method.
$PB_i^{p,q}$	:	weighted product of a solution i expressed using fuzzy normalized weighted geometric Bonferroni mean (NWGBM) in fuzzy-CoCoSo method.
k_i	:	final score of the solution i estimated by three appraisal scores k_{ia}, k_{ib}, and k_{ic} in fuzzy-CoCoSo method.

2.3.2. Fuzzy Best-Worst Method (BWM)

The BWM, first introduced by (Rezaei, 2015), is a multi-criteria decision-making method based on pairwise comparisons for assessing criteria. The BWM, quite different from AHP, only require reference pairwise comparisons, that is only the priority of best criterion over all other criteria and the preference of all the criteria over the worst criterion by using a scale between 1 to 9. Compared to AHP, which involves a full pairwise comparison, BWM provides higher consistency, reduces cognitive burden, and delivers more reliable estimates, making it superior especially in studies involving large number of criteria. This method – being much easier, more accurate, and less redundant as it does not perform secondary pairwise comparisons – has gained much attention in recent times. Considering ambiguity and uncertainty in decision makers' qualitative judgments, a Fuzzy-BWM approach (Guo and Zhao, 2017) with trapezoidal fuzzy numbers was adopted. The steps involved in this method as well as the derivation of consistency index for trapezoidal fuzzy-BWM are described in the Appendix A2. Table 2.3 presents the values of 5-point scale trapezoidal fuzzy spectrum used in this study and Table 2.4 enlists the derived consistency indexes for the respective trapezoidal fuzzy membership functions.

Table 2.3 Transformation rules for the linguistic measures of importance.

Linguistic terms	Membership function (*l, m, n, u*)	Score index
Absolutely important (AI)	(8, 17/2, 9, 9)	9
Very important (VI)	(6, 13/2, 15/2, 8)	7
Fairly important (FI)	(4, 9/2, 11/2, 6)	5
Weakly important (WI)	(2, 5/2, 7/2, 4)	3
Equally important (EI)	(1, 1, 1, 1)	1

Table 2.4 Consistency index (CI) for TrFN-based fuzzy BWM.

Linguistic terms	Membership function (*l, m, n, u*)	CI
Absolutely important (AI)	(8, 17/2, 9, 9)	13.77
Very important (VI)	(6, 13/2, 15/2, 8)	12.58
Fairly important (FI)	(4, 9/2, 11/2, 6)	10
Weakly important (WI)	(2, 5/2, 7/2, 4)	7.37
Equally important (EI)	(1, 1, 1, 1)	3

2.3.3. Fuzzy Combined Compromise Solution (CoCoSo) Method

The CoCoSo method for MCDM was recently proposed by (Yazdani et al., 2019). This technique is considered as the most flexible ranking method compared to other MCDM methods and superior for ranking because, as the name suggests, it presents compromise combination solution (Yazdani et al., 2019). The CoCoSo method integrates weighted sum model (WSM) and weighted product model (WPM) in ranking the alternatives (i.e., solutions). The idea is to combine three MCDM methods namely, simple additive weighting (SAW), weighted aggregated sum product assessment (WASPAS) and multiplicative exponential weighting (MEW) to achieve consistent and multifaceted solution which remains unaffected by variation in criteria (in this case, barriers) weights (Lahane and Kant, 2021).

In this chapter, a modified version of CoCoSo model with application of Bonferroni mean (BM) operator was used to aggregate and estimate the criteria functions weighted sum (SB_i)

and weighted product (PB_i). In original CoCoSo model, these values are calculated using two methods: WSM and WPM. These models impart the values of criteria functions in the cases of the uniform values of alternatives. However, in cases where there are extreme deviations between the values of the most impactful criteria, the criteria function values increase disproportionately. This requires due attention especially in cases where some evaluations of the initial decision matrix may distort the result of aggregation, which may lead to wrong decisions (Dodgson et al., 2009). This distortion can be because of measurement errors or biasness in experts' evaluations. In real world decision-making, such inconsistencies are required to be eliminated. It is necessary to incorporate mechanisms (e.g., BM operators in this study) which consider attribute relationships and diminish the impact of awkward data, which is ignored in WSM and WPM functions. The computational procedure followed in this study is described in Appendix A3. Table 2.5 displays the trapezoidal fuzzy linguistic scale used for evaluating solutions in the current study.

Table 2.5 The fuzzy linguistic scale for evaluating the solutions.

Linguistic terms	**Membership function (*l, m, n, u*)**
Not Impactful	(0, 0, 0.1, 0.3)
Slightly Impactful	(0.1, 0.3, 0.3, 0.5)
Fairly Impactful	(0.3, 0.5, 0.5, 0.7)
Impactful	(0.5, 0.7, 0.7, 0.9)
Very Impactful	(0.7, 0.9, 1, 1)

3. Case study of the proposed method

This section describes the application of the proposed MCDM methodology using the judgements of 12 experts. Firstly, the optimum weights of SEMS barriers and sub-barriers were calculated using the illustrated fuzzy-BWM methodology. Then, based on the obtained weights and experts' evaluations, the scores were determined using fuzzy-CoCoSo method to rank the policy solutions. The calculation process is as follows (readers are requested to see the referenced equations in Appendix):

3.1. Estimation of relative weights of barriers

To estimate the relative weights of 5 barriers and 30 sub-barriers, firstly, individual experts have identified the most and the least critical SEMS barriers and sub-barriers. Then, the pairwise comparison has been performed for each criterion with respect to the best and worst criterion using the linguistic evaluation terms defined in Table 2.3. This would ultimately provide the Best-to-Others and Others-to-Worst vectors. For illustration purposes, an example calculation from the perspective of Expert 1 relative to *five SEMS barriers* is presented here.

Table 2.6 and Table 2.7 respectively presents the transformed trapezoidal fuzzy Best-to-Others $\left(\tilde{V}_{Bi}\right)$ and Others-to-Worst vectors $\left(\tilde{V}_{iW}\right)$.

Table 2.6 The fuzzy Best-to-Others vector $\tilde{V}_{Bi}$

Other criteria → Best criterion ↓	**Behavioural barriers (B1)**	**Policy & Governance barriers (B2)**	**Infrastructural barriers (B3)**	**Technical barriers (B4)**	**External barriers (B5)**
Behavioural barriers (B1)	(1, 1, 1, 1)	(1, 1, 1, 1)	(2, 5/2, 7/2, 4)	(8, 17/2, 9, 9)	(4, 9/2, 11/2, 6)

Table 2.7 The fuzzy Others-to-Worst vector $\tilde{V}_{iW}$

Worst criterion → Other criteria ↓	**Technical barriers (B4)**
Behavioural barriers (B1)	(8, 17/2, 9, 9)
Policy & Governance barriers (B2)	(6, 13/2, 15/2, 8)
Infrastructural barriers (B3)	(4, 9/2, 11/2, 6)
Technical barriers (B4)	(1, 1, 1, 1)
External barriers (B5)	(2, 5/2, 7/2, 4)

Based on the above vectors (Table 2.6 and Table 2.7) and according to Equation 2.10, the nonlinearly constrained optimization problem can be constructed as follows:

$$\min\ \tilde{\xi}$$

$$s.t.\begin{cases} \left| \dfrac{\left(l_1^w, m_1^w, n_1^w, u_1^w\right)}{\left(l_a^w, m_a^w, n_a^w, u_a^w\right)} - l_{1a}, m_{1a}, n_{1a}, u_{1a} \right| \le \left(k^*, k^*, k^*, k^*\right) \\ \left| \dfrac{\left(l_b^w, m_b^w, n_b^w, u_b^w\right)}{\left(l_4^w, m_4^w, n_4^w, u_4^w\right)} - l_{b4}, m_{b4}, n_{b4}, u_{b4} \right| \le \left(k^*, k^*, k^*, k^*\right) \\ \sum_{i=1}^{5} R\left(\tilde{w}_i\right) = 1 \\ l_i^w \le m_i^w \le n_i^w \le u_i^w;\ l_i^w \ge 0;\ k^* \ge 0 \end{cases}$$

where, $a = 2,3,4,5;\ b = 2,3,5;\ i = 1,2,3,4,5.$

Then, we can obtain the nonlinearly constrained optimization problem represented by concrete numbers as follows:

$$\min \ k*$$

$$s.t.\begin{cases}
l_1-u_2 \le k*u_2; & l_1-u_2 \ge -k*u_2 \\
m_1-n_2 \le k*n_2; & m_1-n_2 \ge -k*n_2 \\
n_1-m_2 \le k*m_2; & n_1-m_2 \ge -k*m_2 \\
u_1-l_2 \le k*l_2; & u_1-l_2 \ge -k*l_2 \\
l_1-4*u_3 \le k*u_3; & l_1-4*u_3 \ge -k*u_3 \\
m_1-3.5*n_3 \le k*n_3; & m_1-3.5*n_3 \ge -k*n_3 \\
n_1-2.5*m_3 \le k*m_3; & n_1-2.5*m_3 \ge -k*m_3 \\
u_1-2*l_3 \le k*l_3; & u_1-2*l_3 \ge -k*l_3 \\
l_1-9*u_4 \le k*u_4; & l_1-9*u_4 \ge -k*u_4 \\
m_1-9*n_4 \le k*n_4; & m_1-9*n_4 \ge -k*n_4 \\
n_1-8.5*m_4 \le k*m_4; & n_1-8.5*m_4 \ge -k*m_4 \\
u_1-8*l_4 \le k*l_4; & u_1-8*l_4 \ge -k*l_4 \\
l_1-6*u_5 \le k*u_5; & l_1-6*u_5 \ge -k*u_5 \\
m_1-5.5*n_5 \le k*n_5; & m_1-5.5*n_5 \ge -k*n_5 \\
n_1-4.5*m_5 \le k*m_5; & n_1-4.5*m_5 \ge -k*m_5 \\
u_1-4*l_5 \le k*l_5; & u_1-4*l_5 \ge -k*l_5 \\
l_2-8*u_4 \le k*u_4; & l_2-8*u_4 \ge -k*u_4 \\
m_2-7.5*n_4 \le k*n_4; & m_2-7.5*n_4 \ge -k*n_4 \\
n_2-6.5*m_4 \le k*m_4; & n_2-6.5*m_4 \ge -k*m_4 \\
u_2-6*l_4 \le k*l_4; & u_2-6*l_4 \ge -k*l_4 \\
l_3-6*u_4 \le k*u_4; & l_3-6*u_4 \ge -k*u_4 \\
m_3-5.5*n_4 \le k*n_4; & m_3-5.5*n_4 \ge -k*n_4 \\
n_3-4.5*m_4 \le k*m_4; & n_3-4.5*m_4 \ge -k*m_4 \\
u_3-4*l_4 \le k*l_4; & u_3-4*l_4 \ge -k*l_4 \\
l_5-4*u_4 \le k*u_4; & l_5-4*u_4 \ge -k*u_4 \\
m_5-3.5*n_4 \le k*n_4; & m_5-3.5*n_4 \ge -k*n_4 \\
n_5-2.5*m_4 \le k*m_4; & n_5-2.5*m_4 \ge -k*m_4 \\
u_5-2*l_4 \le k*l_4; & u_5-2*l_4 \ge -k*l_4 \\
\sum_{i=1}^{5}\left(\dfrac{l_i+2m_i+2n_i+u_i}{6}\right)=1; & \\
0 \le l_i \le m_i \le n_i \le u_i \le 1, \ i=1,2,3,4,5 & \\
k \ge 0 &
\end{cases}$$

By solving this optimization problem, the optimal trapezoidal fuzzy weights of five barriers {'Behavioural', 'Policy & Governance', 'Infrastructural' 'Technical', 'External'} for Expert 1 can be estimated, which are:

$\tilde{w}_1^* = (0.4023, 0.4023, 0.4023, 0.4023);$
$\tilde{w}_2^* = (0.2690, 0.2793, 0.2900, 0.3051);$
$\tilde{w}_3^* = (0.1768, 0.1768, 0.1768, 0.1768);$
$\tilde{w}_4^* = (0.0414, 0.0414, 0.0414, 0.0414);$
$\tilde{w}_5^* = (0.0941, 0.0941, 0.0941, 0.0941);$
$k^* = (1.7251, 1.7251, 1.7251, 1.7251)$

Considering $\tilde{v}_{BW} = \tilde{v}_{14} = (8, 17/2, 9, 9)$, the consistency index (CI) for this case is 13.77 and the consistency ratio is $CR = 1.7251/13.77 = 1.125$. As this value close to zero, the pairwise comparisons are considered consistent. Subsequently, the optimal fuzzy weights for all sub-barriers within each category were calculated. The crisp weights (GMIRs) of all the barriers and sub-barriers were then calculated using the Equation 2.13. Thereafter, final local fuzzy weights of SEMS barriers and sub-barriers were calculated by taking arithmetic mean of the local weights obtained from each expert's evaluation. Further, the global weights of sub-barriers were computed as a product of weight of corresponding primary category of SEMS barrier with the respective weights of sub-barriers. Finally, each of the sub-barriers was assigned with global rank according to their global weights (highest weight was assigned to global rank one). Table 2.8 presents the overall final defuzzified weights and ranks for barriers and sub-barriers. Figure 2.2 graphically presents the individual and cumulative weights of SEMS sub-barriers. It suggests that first 10 ranked sub-barriers account for 50% of the total weightage, while first 20 ranked sub-barriers contribute to 81% of total representation. It is also observed that these 20 sub-barriers represent all five main categories of SEMS barriers while most of the first 10 sub-barriers correspond to either Behavioural barriers or Policy & governance barriers. This includes habit of using private modes (B13), higher perceived cost (B16), little awareness about SEMS (B11), lack of vision and policies (B21), less suitable according to demographics (B51), negative perception of SEMS (B12), accessibility and availability at origin (B33), no fulfilment of trip requirements (B52), lack of capital required (B24), coordination issues between involved authorities (B26).

Table 2.8 Weights and ranking of SEMS barriers and sub-barriers.

Main barriers	**Weight of main barriers**	**Sub-barriers**	**Local weight of sub-barriers***	**Local ranking**	**Global weight of sub-barriers***	**Global ranking**
Behavioural barriers (B1)	0.300	B11	16.95	3	5.09	3
		B12	14.91	4	4.48	6
		B13	33.51	1	10.07	1

		B14	6.20	6	1.86	26
		B15	11.16	5	3.35	12
		B16	17.27	2	5.19	2
Policy & Governance barriers (B2)	0.227	B21	22.28	1	5.06	4
		B22	9.68	6	2.20	23
		B23	11.66	5	2.65	20
		B24	16.72	2	3.80	9
		B25	9.48	7	2.15	24
		B26	16.03	3	3.64	10
		B27	14.15	4	3.21	14
Infrastructural barriers (B3)	0.222	B31	15.62	2	3.47	11
		B32	10.67	6	2.37	22
		B33	18.89	1	4.20	7
		B34	13.10	4	2.91	17
		B35	15.01	3	3.33	13
		B36	10.80	5	2.40	21
		B37	7.95	8	1.77	28
		B38	7.97	7	1.77	27
Technical barriers (B4)	0.102	B41	20.65	3	2.10	25
		B42	27.07	2	2.76	19
		B43	28.05	1	2.85	18
		B44	10.66	5	1.08	30
		B45	13.57	4	1.38	29
External barriers (B5)	0.149	B51	30.84	1	4.58	5
		B52	27.76	2	4.12	8
		B53	21.51	3	3.19	15
		B54	19.89	4	2.95	16

*Represented as percentage of contribution

3.2. Estimation of rank of policy solutions

As mentioned earlier, the final weights of sub-barriers were used to evaluate and estimate the rank of policy solutions using the fuzzy-CoCoSo method. A list of selected policy solutions is presented in Table 2.2. The evaluation of the solutions against each sub-barrier was carried out by the experts using the linguistic scale presented in Table 2.5. These evaluations were then transformed into the fuzzy trapezoidal numbers by using the membership functions mentioned in Table 2.5. These two steps yielded an initial decision matrix and a fuzzy decision matrix respectively for each expert. The initial aggregated fuzzy decision matrix was obtained by arithmetically averaging the corresponding values of individual experts' decision matrices, glimpse of which is presented in Table 2.9. Then, this initial fuzzy decision matrix was transformed into the fuzzy normalized matrix whose elements were calculated using Equation 2.15. It is shown in Table 2.10. Please note that only the formula for *benefit-criteria* is used in calculation since all the selected policy solutions influence positively on SEMS uptake. Following that, the values of weighted sum SB_i and weighted product PB_i for all solutions were calculated by applying the NWBM (Equation 2.16) and NWGBM (Equation 2.17) and subsequently, the crisp values of SB_i and PB_i were obtained using GMIR formula mentioned in Equation 2.5. The values of SB_i and PB_i were estimated considering the values of parameters $p = q = 1$.

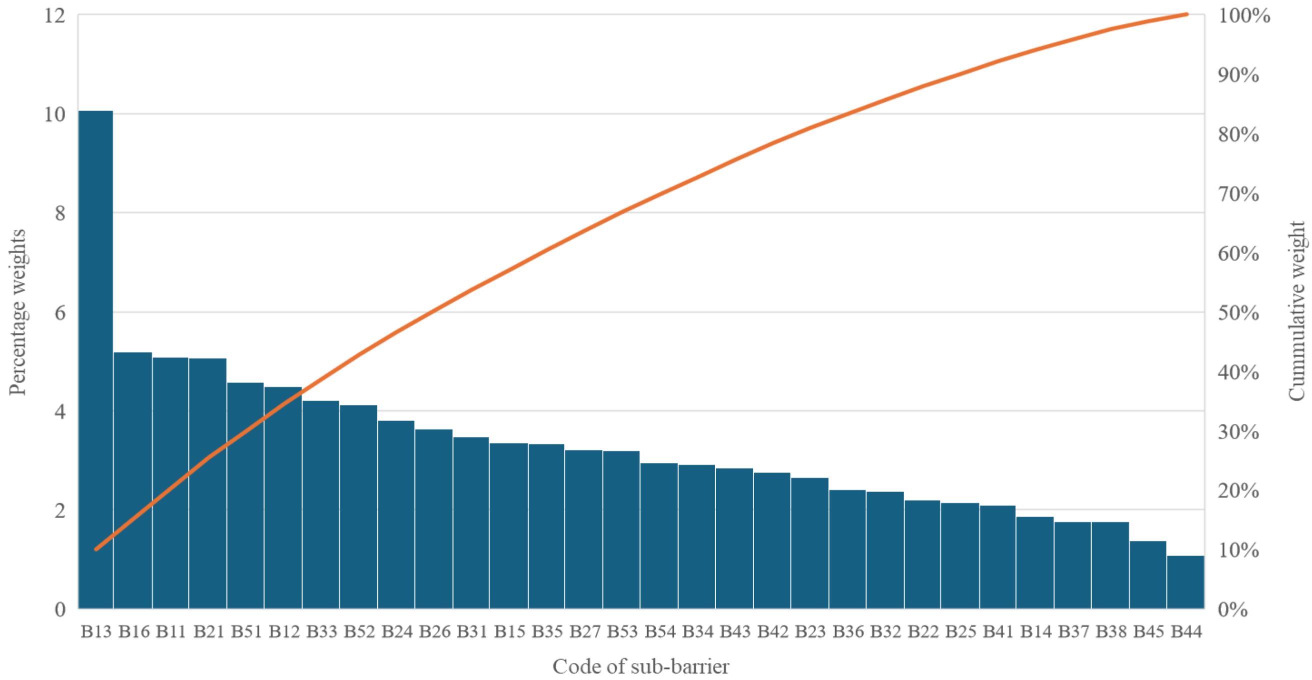

Figure 2.2 Individual and cumulative global weights of sub-barriers.

Finally, the relative weights of the policy solutions, k_{ia}, k_{ib}, and k_{ic}, were obtained by applying three appraisal scoring strategies (Equation 2.18, 2.19, and 2.20). In Equation 2.20, the value of coefficient λ was taken to be 0.5. Using Equation 2.21, the final ranking score for each solution,

k_i, is determined. All these estimated parameters and final rank of respective solutions are displayed in Table 2.11 and graphically represented in Figure 2.3. The policy solution with the highest k_i is chosen as the most influential solution (i.e., it should be preferred ahead of other solutions).

3.3. Sensitivity analysis

In this sub-section, the results obtained through proposed fuzzy-MCDM model are validated to assess the robustness of the results. The validation is performed through two different scenarios. In the first scenario, the impact of changing the weight of Behavioural barrier (which has the highest weightage amongst five main category barriers) is analysed to discuss the effect of criteria (i.e., barriers) fluctuation on ranking of policy solutions. In the second scenario, the effect of changing the parameter λ ($0 \leq \lambda \leq 1$) on solutions' final score k_i is analysed by varying the values of λ.

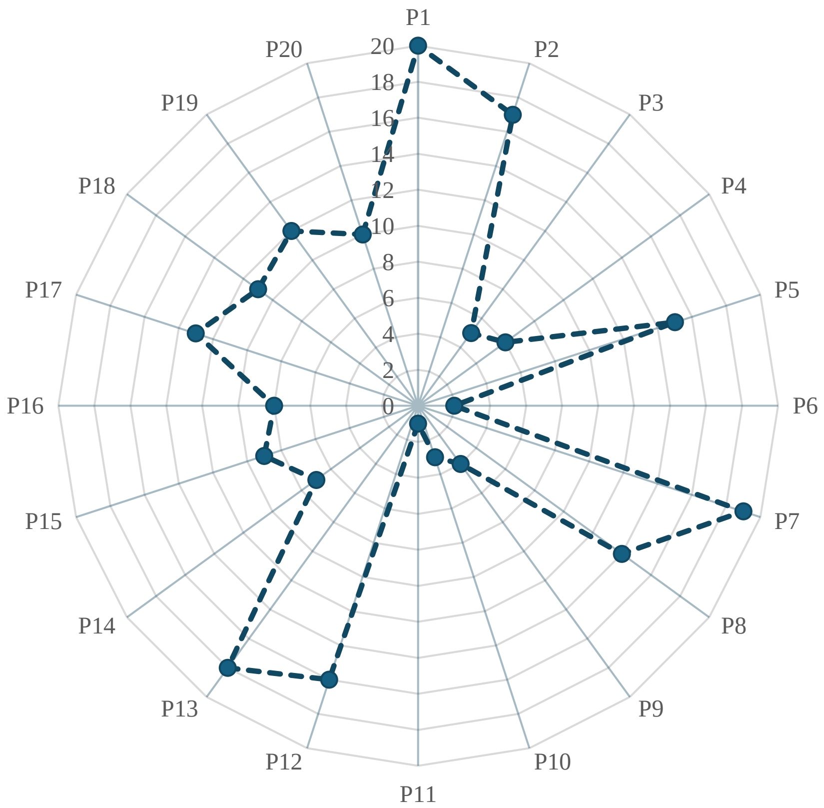

Figure 2.3 Ranking order of policy solutions

Table 2.9 The initial aggregated fuzzy decision matrix.

	B11	**B12**	**B13**	···	···	···	**B53**	**B54**
P1	(0.14,0.23,0.28,0.48)	(0.06,0.15,0.21,0.41)	(0.39,0.59,0.62,0.76)	···	···	···	(0.05,0.06,0.15,0.35)	(0.21,0.34,0.38,0.56)
P2	(0.13,0.24,0.28,0.48)	(0.11,0.22,0.26,0.46)	(0.52,0.72,0.75,0.89)	···	···	···	(0.06,0.08,0.18,0.36)	(0.13,0.24,0.28,0.48)
P3	(0.57,0.77,0.84,0.91)	(0.52,0.72,0.75,0.88)	(0.48,0.68,0.71,0.85)	···	···	···	(0.13,0.20,0.26,0.46)	(0.21,0.34,0.37,0.57)
P4	(0.54,0.74,0.79,0.88)	(0.47,0.65,0.70,0.83)	(0.38,0.56,0.59,0.75)	···	···	···	(0.13,0.20,0.26,0.46)	(0.21,0.34,0.38,0.56)
P5	(0.10,0.19,0.25,0.45)	(0.14,0.26,0.30,0.50)	(0.08,0.14,0.21,0.41)	···	···	···	(0.10,0.15,0.24,0.42)	(0.07,0.15,0.21,0.41)
P6	(0.09,0.13,0.22,0.40)	(0.12,0.25,0.28,0.48)	(0.11,0.18,0.25,0.45)	···	···	···	(0.11,0.18,0.25,0.45)	(0.14,0.23,0.29,0.47)
···	···	···	···	···	···	···	···	···
···	···	···	···	···	···	···	···	···
···	···	···	···	···	···	···	···	···
P16	(0.10,0.19,0.25,0.45)	(0.17,0.34,0.35,0.55)	(0.13,0.24,0.29,0.47)	···	···	···	(0.07,0.11,0.20,0.38)	(0.06,0.12,0.19,0.39)
P17	(0.04,0.11,0.17,0.37)	(0.07,0.15,0.21,0.41)	(0.09,0.20,0.25,0.45)	···	···	···	(0.07,0.11,0.19,0.39)	(0.05,0.09,0.17,0.37)
P18	(0.19,0.32,0.36,0.55)	(0.30,0.50,0.50,0.70)	(0.24,0.42,0.43,0.63)	···	···	···	(0.12,0.17,0.25,0.45)	(0.10,0.15,0.23,0.43)
P19	(0.23,0.35,0.40,0.58)	(0.32,0.52,0.54,0.70)	(0.19,0.32,0.36,0.55)	···	···	···	(0.09,0.13,0.21,0.41)	(0.12,0.17,0.25,0.44)
P20	(0.28,0.45,0.46,0.66)	(0.31,0.49,0.51,0.69)	(0.17,0.34,0.35,0.55)	···	···	···	(0.07,0.11,0.19,0.39)	(0.05,0.10,0.17,0.37)

Table 2.10 Fuzzy normalized matrix.

	B11	B12	B13	···	···	···	B53	B54
P1	(0.15,0.25,0.31,0.53)	(0.07,0.18,0.24,0.46)	(0.44,0.66,0.69,0.86)	···	···	···	(0.09,0.12,0.30,0.68	(0.35,0.57,0.65,0.95)
P2	(0.14,0.26,0.31,0.53)	(0.12,0.25,0.30,0.53)	(0.58,0.81,0.84,1.00)	···	···	···	(0.12,0.16,0.35,0.70)	(0.22,0.40,0.48,0.82)
P3	(0.63,0.85,0.9,1.00)	(0.59,0.81,0.86,1.00)	(0.54,0.77,0.80,0.96)	···	···	···	(0.25,0.39,0.51,0.89)	(0.35,0.57,0.63,0.97)
P4	(0.59,0.81,0.87,0.97	(0.54,0.74,0.79,0.94)	(0.43,0.63,0.66,0.85)	···	···	···	(0.25,0.39,0.51,0.89)	(0.35,0.57,0.65,0.95)
P5	(0.11,0.21,0.27,0.49)	(0.15,0.30,0.34,0.57)	(0.09,0.15,0.23,0.46)	···	···	···	(0.19,0.30,0.46,0.81)	(0.12,0.25,0.35,0.69)
P6	(0.10,0.14,0.24,0.44)	(0.13,0.28,0.32,0.55)	(0.12,0.20,0.28,0.50)	···	···	···	(0.21,0.35,0.47,0.86)	(0.23,0.38,0.49,0.80)
···	···	···	···	···	···	···	···	···
···	···	···	···	···	···	···	···	···
···	···	···	···	···	···	···	···	···
P16	(0.11,0.21,0.27,0.49)	(0.20,0.38,0.40,0.63)	(0.14,0.27,0.33,0.53)	···	···	···	(0.14,0.21,0.39,0.74)	(0.11,0.20,0.32,0.66)
P17	(0.04,0.12,0.19,0.41	(0.08,0.16,0.24,0.46)	(0.10,0.22,0.28,0.50)	···	···	···	(0.14,0.21,0.37,0.75)	(0.09,0.15,0.29,0.63)
P18	(0.21,0.35,0.40,0.60)	(0.34,0.57,0.57,0.79)	(0.27,0.47,0.48,0.70)	···	···	···	(0.23,0.33,0.47,0.86)	(0.17,0.26,0.38,0.72)
P19	(0.25,0.39,0.44,0.64)	(0.36,0.59,0.61,0.79)	(0.21,0.36,0.41,0.61)	···	···	···	(0.18,0.25,0.40,0.79)	(0.20,0.29,0.43,0.74)
P20	(0.31,0.49,0.51,0.73)	(0.35,0.56,0.58,0.78)	(0.19,0.38,0.40,0.62)	···	···	···	(0.14,0.21,0.37,0.75)	(0.08,0.17,0.29,0.63)

Table 2.11 The fuzzy weighted sum and weighted product sequences.

	Fuzzy (SB_i)	Fuzzy (PB_i)	Crisp (SB_i)	Crisp (PB_i)	k_{ia}	k_{ib}	k_{ic}	k_i	Rank
P1	(0.18,0.28,0.36,0.61)	(0.16,0.25,0.35,0.60)	0.346	0.326	0.041	2.000	0.657	1.278	20
P2	(0.18,0.29,0.37,0.62)	(0.16,0.27,0.36,0.61)	0.356	0.336	0.042	2.058	0.676	1.315	17
P3	(0.26,0.41,0.48,0.71)	(0.22,0.36,0.45,0.69)	0.457	0.422	0.054	2.613	0.859	1.670	5
P4	(0.26,0.40,0.47,0.70)	(0.23,0.37,0.45,0.69)	0.451	0.424	0.054	2.602	0.855	1.663	6
P5	(0.17,0.31,0.37,0.62)	(0.17,0.30,0.36,0.62)	0.359	0.352	0.044	2.116	0.695	1.352	15
P6	(0.28,0.45,0.50,0.74)	(0.27,0.43,0.49,0.73)	0.488	0.471	0.059	2.855	0.938	1.824	2
P7	(0.18,0.30,0.37,0.62)	(0.15,0.26,0.35,0.61)	0.356	0.331	0.042	2.042	0.671	1.305	19
P8	(0.19,0.31,0.38,0.63)	(0.16,0.28,0.36,0.62)	0.368	0.344	0.044	2.120	0.697	1.355	14
P9	(0.27,0.42,0.48,0.71)	(0.25,0.40,0.47,0.71)	0.463	0.448	0.056	2.710	0.890	1.731	4
P10	(0.26,0.44,0.49,0.73)	(0.25,0.43,0.48,0.72)	0.474	0.466	0.058	2.797	0.919	1.787	3
P11	(0.31,0.48,0.53,0.77)	(0.30,0.47,0.52,0.76)	0.516	0.507	0.063	3.044	1.000	1.945	1
P12	(0.17,0.30,0.37,0.62)	(0.16,0.29,0.36,0.61)	0.353	0.343	0.043	2.073	0.681	1.324	16
P13	(0.17,0.29,0.36,0.61)	(0.16,0.28,0.35,0.61)	0.350	0.339	0.042	2.050	0.674	1.310	18
P14	(0.24,0.40,0.46,0.70)	(0.23,0.39,0.45,0.69)	0.441	0.433	0.054	2.601	0.854	1.662	7
P15	(0.24,0.39,0.45,0.69)	(0.23,0.38,0.45,0.68)	0.436	0.429	0.053	2.575	0.846	1.645	9
P16	(0.24,0.40,0.46,0.70)	(0.23,0.39,0.45,0.69)	0.441	0.430	0.053	2.592	0.852	1.656	8
P17	(0.20,0.34,0.40,0.65)	(0.18,0.32,0.39,0.64)	0.388	0.372	0.047	2.259	0.743	1.444	13
P18	(0.23,0.37,0.44,0.68)	(0.22,0.35,0.43,0.67)	0.422	0.406	0.051	2.466	0.810	1.575	11
P19	(0.22,0.37,0.43,0.67)	(0.21,0.35,0.42,0.66)	0.415	0.405	0.050	2.439	0.801	1.558	12
P20	(0.23,0.38,0.44,0.68)	(0.22,0.37,0.43,0.68)	0.425	0.415	0.052	2.500	0.821	1.597	10

3.3.1. Impact of variation in weight of barrier

For analysing the effect of fluctuation in weight of main barrier, seven scenarios are created by varying the weight of Behavioural barrier (=0.300) to 70%, 80%, 90%, 100% (base), 110%, 120% and 130% of the obtained weight. It is obvious that the reduction or increment of 10%, 20% or 30% in barrier weight leads to corresponding change in weights of barriers and sub-barriers so that the sum of all weights is 1. Considering the initial weight of Behavioural barrier W_1^* is changed to αW_1^*, where $\alpha = \{0.7, 0.8, 0.9, 1, 1.1, 1.2, 1.3\}$, the weights of other main barriers can be converted as $\beta W_j^*, j = 2, 3, 4, 5$. The values of α and β satisfies the condition $\alpha W_1^* + \sum_{j=2}^{5} \beta W_j^* = 1$. Therefore, the weights of other main barriers can be calculated according to $\beta = \left(1 - \alpha W_1^*\right) / \left(1 - W_1^*\right)$. Subsequently, the updated weights of all sub-barriers can be obtained based on the weights of main barriers.

The ranking of twenty policy solutions corresponding to each scenario is presented in Figure 2.4. It can be observed that the change in weight of Behavioural barrier has minimal effects on the ranking of policy solutions. For all scenarios, solutions P11, P6, P10 and P9 still remain the top four and superior to other solutions while P1 remains the bottommost. The order of a few of the solutions fluctuate only slightly, i.e., in the range of 2. The overall results indicate considerable consistency and credibility suggesting that the MCDM model proposed in this chapter is suitable and effective. Besides, it can be noted that the rank of P2 increases from 18 to 16 when weight increases from 70% to 130%. This is logical since solution P2 – "Establishment of parking restriction policies" – can positively affect the SEMS adoption from behavioural perspective. The same has been observed for P8 (transport pricing), and with opposite nature for P12 and P13 since they both are technical solutions with minimal direct effects on behaviour. The result of this nature further supports the robustness of the proposed model.

3.3.2. Impact of change in parameter λ

Since the value of parameter λ ranges in an interval [0,1], the value of λ was varied ranging from 0 continued till 1 with an increment of 0.1. The impact of the value of the coefficient λ on the values of final scores k_i is represented in Figure 2.5. Based on the chart, it can be observed that variation in the parameter λ has minimal effects on the values of k_i. And they are not significant enough to alter the rankings of policy solutions. It clearly defines the validity and credibility of the obtained results.

All in all, the overall results of the sensitivity analysis for both the cases depict no to minimal effects on the final rankings of the policy solutions. For all the scenarios, no matter how the weight of main barrier changes and the values of the coefficient λ varies, P1 – P4 always remain the top four policy solutions. Further P17 – P20 remain the bottommost for most cases. Readers should note the fact that the influence of the coefficient λ on the final score k_i is directly relied upon the elements of initial decision matrix. Therefore, for the other values of the elements in the initial decision matrix, this influence can significantly change the ranks. The same can be opined for the change in barrier weights as well.

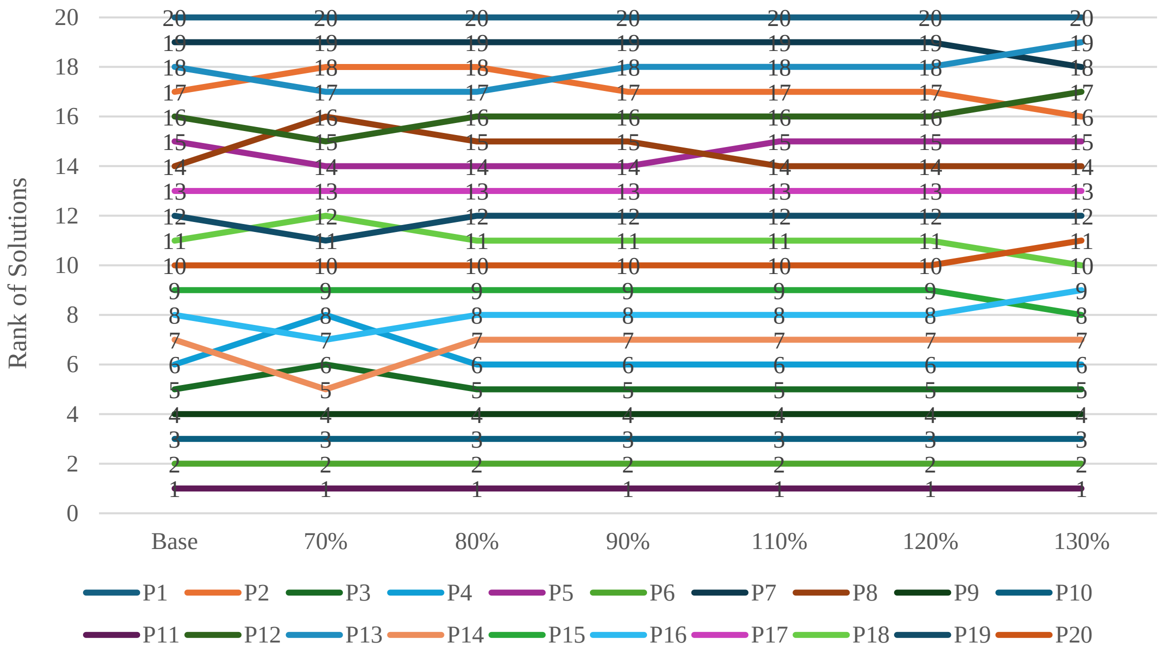

Figure 2.4 Sensitivity analysis result of change in weight of Behavioural barrier.

4. Discussion

An integrated two-phase multi-criteria decision-making method was applied in this research to investigate adoption of SEMS at macro level. The fuzzy BWM was employed to estimate the weightages of various SEMS barriers and corresponding sub-barriers. Following that, selected policy-level solutions were ranked using fuzzy CoCoSo technique to understand their influence on overcoming the barriers. This section briefly discusses the obtained results and address the potential implications to realise the full potential of shared electric mobility services for sustainable transportation.

4.1. Barriers to shared electric mobility adoption

According to the experts' opinion analysis, Behavioural barriers (percentage normalized weight = 30%) have the highest estimated weightage amongst five main category barriers, followed by Policy & governance barriers (22.7%) and Infrastructural barriers (22.2%) which account for nearly equal weightage. External barriers (14.9%) and Technical barriers (10.2%) collectively account for about 25% of the total weightage. The sequence of sub-barriers according to their global weights can be presented as follows:

$B13 > B16 > B11 > B21 > B51 > B12 > B33 > B52 > B24 > B26 > B31 > B15 > B35 > B27 > B53 > B54 > B34 > B43 > B42 > B23 > B36 > B32 > B22 > B25 > B41 > B14 > B38 > B37 > B45 > B44$

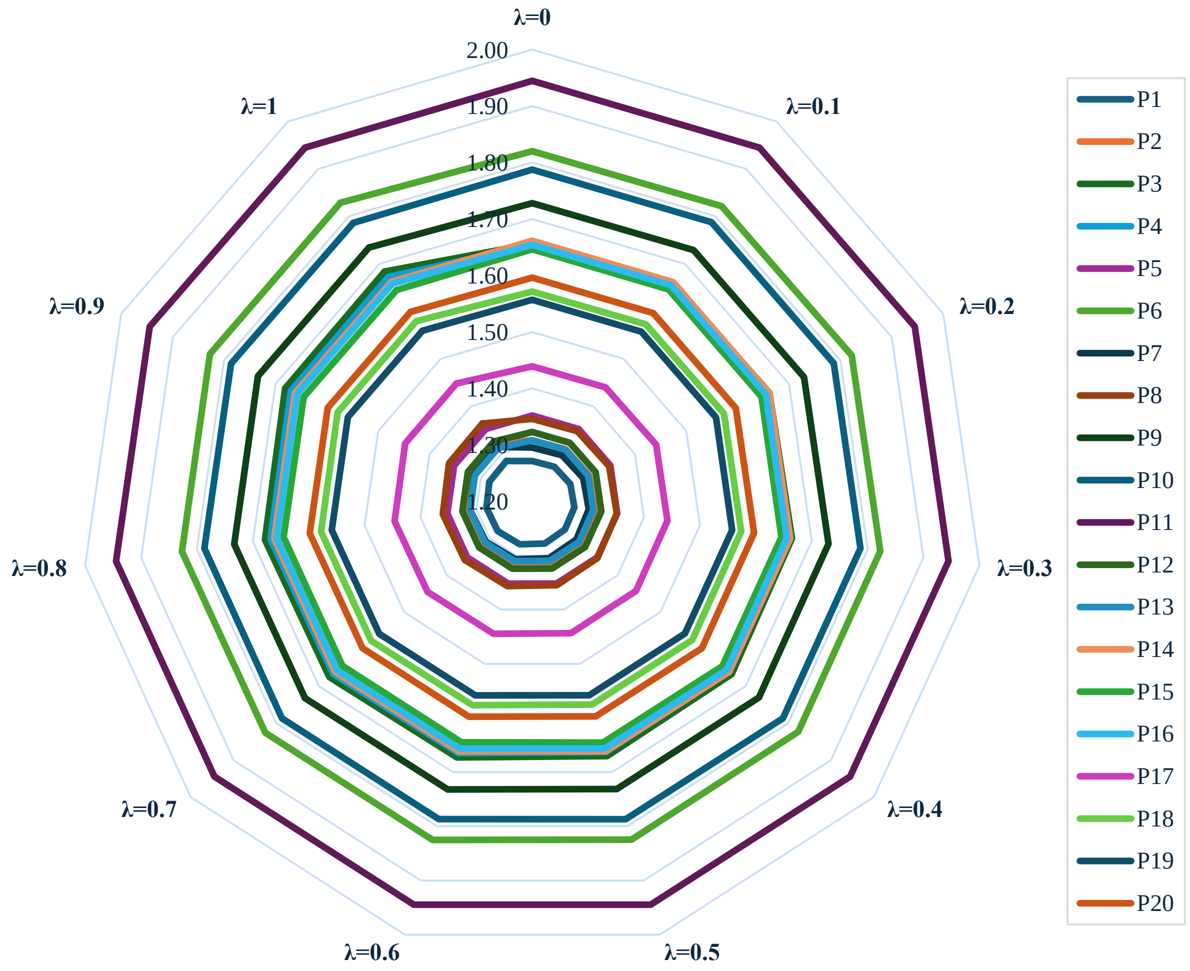

Figure 2.5 Sensitivity analysis result of change in the coefficient λ.

Within the Behavioural barriers, "the habit of using private mode of transport (B13)" is the most critical sub-barrier with category weightage of 33.5%. It is also the highest ranked sub-barrier globally with 10% weightage amongst 30 identified sub-barriers. An already-established travel habits plays an important role during decision-making regarding travel mode. Several studies investigating the psychological or attitudinal factors of the travellers have addressed the difficulty in breaking these habits while considering the adoption of new-age mobility services (Bretones and Marquet, 2022; De Witte et al., 2013; Pellegrini and Tagliabue, 2024; Van Acker et al., 2010). Further, "Higher perceived cost to the users (B16)" and "Little awareness about the SEMS technology and its benefits (B11)" are respectively second and third highest globally ranked sub-barriers. The monetary cost is one the most frequently cited determinants in adoption and usage of shared e-mobility. Studies have found that individuals seem to be uncertain or sceptical regarding whether the shared modes are comparatively cheaper solution or not (Bateman et al., 2021a; Esztergár-Kiss and Lopez Lizarraga, 2021;

Nematchoua et al., 2020a). The awareness knowledge and enthusiasm towards the sharing system is also well highlighted by the researchers in context of SEMS (Bösehans, et al., 2023; Bretones & Marquet, 2022)

Policy and governance barriers is the second-highest ranked category among the main barriers. It was observed that sub-barriers such as “Lack of future visions, priorities, and coherent & nationwide policy (B21)” and “Lack of required capital investments for developments and operations (B24)” are among the key barriers in this category which can play important role in effective implementation and uptake of SEMS. A report for Transport and Environment corroborates our findings which posed the challenges arise from the differing policies and attitudes towards shared vehicle services (Tyrer and Orchard, 2021). Fragmented policies and a lack of coherent planning across local authorities and governing bodies can lead to complications in services, operations and expansions of the schemes and making it difficult to access local infrastructure required for shared electric mobility systems to thrive. This inconsistency can deter investors and users due to uncertain future conditions and lack of reliable incentives, which hinders widespread adoption (Sperling and Gordon, 2009). Besides, the high upfront cost for setting up the infrastructure coupled with inadequate financial incentives, such as grants and subsidies can deter private investors and local authorities from committing to SEMS projects. Operators need to balance operational costs with revenue, which is often unpredictable in the early stages. Insufficient capital investment can lead to underdeveloped systems, further reducing user adoption rates.

Infrastructural barriers has the third highest weightage amongst the main category barriers. According to the results, “Access to and availability of SEMS at origin (B33)”, “Un(/less) suitable city infrastructure at current levels (B33),” and “Unavailability of required space (B35)” are most critical sub-barriers with respective local weights of 18.9%, 15.6%, and 15%. Researchers have highlighted the importance of accessibility to shared mobility stations and availability of shared vehicles when needed in context of station-based shared mobility services (Aydin et al., 2022; Curtale and Liao, 2023a; Liao et al., 2024). It is quite obvious that closer SEMS station locations tend to attract more users. However, it is equally desirable that the shared EVs are consistently available to users when needed. Without adequate vehicle relocation mechanism and charging infrastructure to meet the demand, it is possible that certain stations may experience a shortage which lead to delays and increased waiting time. Further, many cities lack the necessary infrastructure, such as dedicated charging stations and exclusive micromobility lanes, to support smooth operations of SEMS services and safe riding in heterogeneous traffic conditions. Additionally, the existing urban infrastructure often lacks the capacity to support a high density of charging stations, leading to congestion and inadequate charging facilities (Vaidya and Mouftah, 2020). Such conditions limit the scalability of the shared electric mobility services.

External barriers such as “Less suitable according to the individuals’ demographics (B51)” and “No fulfilments of trip requirements – higher trip length, greater travel time, multiple destinations enroute (B52)” can also impact significantly on the SEMS adoption. The needs of particular group of people, such as elders, families with specific needs for young children (e.g., seats), those requiring configurations for disabilities, or people who are not digitally active. Lastly, within Technical barriers, “Poor integration with public transport systems – accessibility and fare system (B43)” and “Uncertain availability – due to inefficient charging infrastructure and larger charging layovers – limits the supply (B42)” are the most influential sub-barriers with category weight of 28% and 27% respectively. Research highlights the issue of low physical integration with public transport, which contributes to the difficulties in accessing shared EVs particularly for the users who desire to take electric micromobility modes for their access/egress to public transport. The lack of coordination between shared mobility services and public transportation, or in other words, when the synergy between the two systems is not considered properly, it makes difficult for the users to access shared electric mobility when required (Coenegrachts et al., 2021; Oeschger et al., 2020).

4.2. Policy implications

As mentioned earlier in this chapter, total twenty policy-level solutions have been identified to overcome the SEMS barriers. Based on the proposed fuzzy-CoCoSo analysis, the sequence of policy solutions according to their relative significance scores is as follows:

$$P11 > P6 > P10 > P9 > P3 > P4 > P14 > P16 > P15 > P20 > P18 > P19 > P17 > P8 >$$
$$P5 > P12 > P2 > P13 > P7 > P1$$

The findings of the present work suggest that “Development of financial strategies to implement quality network for micro-mobility routes and to eliminate missing links (P11)” is the highest ranked and therefore the most influential amongst the selected solutions. Because of the lack of robust regulatory framework and coherent policy for shared and electric mobility at current juncture, such services have not been widely established and adopted despite their potential to improve transport system efficiency and sustainability. It is crucial to strategically invest in micro-mobility infrastructure which requires substantial funding. The effective financial strategies may include public-private partnerships (PPPs) leveraging both public funding and private investment to build and maintain infrastructure, grants and subsidies from government authorities to incentivize the developments (e.g., European union’s PROMETHEUS), easier access to finance with flexible terms for entities involved in these technologies and services, formulating shared revenue model integrating shared mobility services with existing public transport to enhance financial viability, and incentives such as discounted usage fees or subscriptions to attract users towards shared electric mobility can be among the key strategies for effective implementation of shared mobility network which ultimately can elevate its usage. Further, a national framework should provide guidance to local authorities on assessing suitability of the transport measures, monitoring the impact of actions taken, and developing charging infrastructure deployment plans to eliminate missing links (Tyrer and Orchard, 2021).

“Prior assessment for the optimal locations for SEMS stations (P6)” is another key consideration for maximizing accessibility and usability of services as it is ranked second highest in our analysis. It is important that SEMS stations are strategically placed near high density residential areas, business districts, and popular destinations to ensure they are within easy reach for users at origin and destination. Integrating SEMS with public transport hubs can facilitate multimodal travel and encourage the use of shared electric modes complementary to the public transport. Furthermore, it is imperative to understand the peak hour supply, popular routes as well as areas with limited public transport options to cope with the users' mobility needs and demand.

Approaching "Established policies towards transit-oriented development and 15-minutes city (P10)" can reduce reliance on private vehicles, making shared mobility options, particularly micro-modes, more attractive and feasible. As mentioned before, investing in extensive micromobility network coupled with strategically placing SEMS stations within neighbourhoods can support the use of shared electric mobility. In that line, promoting and regulating mixed-use developments ensures commercial and recreational areas are closely integrated with residential areas which can reduce travel distances and foster SEMS usage.

Next, "Improvements in charging infrastructure and its availability (P9)" can greatly reduce the charging layovers and allows vehicles to return to service more quickly. (Roni et al., 2019) showed that increasing the number of fast charging stations reduced the total fleet downtime and travel time during charging trips by 2-4% and 26-49% respectively. Additionally, strategically placed charging stations within the service area can minimize the travel distance to charging points. More advanced techniques such as battery-swapping and in-route wireless charging can virtually eliminate the charging layover times enhancing overall fleet efficiency (Mohamed et al., 2019).

Furthermore, "Creating awareness campaigns for sustainable transport amongst the citizens (P3)" and "Making people aware of the benefits of using electric shared-vehicles – at individual and societal levels (P4)" are essential to encourage behavioural change and drive the SEMS adoption. As the knowledge gaps significantly impact the adoption rates, tailoring awareness campaigns emphasizing on environmental (e.g., reduced GHG emissions), economic (e.g., zero purchase and maintenance cost), and societal benefits (e.g., reduced congestion, enhanced public health) can encourage individuals to switch to SEMS. Local authorities, in their campaigns, should highlight policy mechanisms that may include infrastructure support, tax exemptions, and strong national targets (such as UK's net zero by 2050) can prove to be effective in accelerating adoption.

Other effective policy-level solutions include "Provisions for supportive local authorities and policies that can aid in effective operations (P14)," "Close coordination between local authorities and operators to better understand the market conditions and requirements and efficient operations (P16)," "Consideration of social equity while planning new infrastructure – to ensure the transport needs of communities irrespective of their social and economic characteristics (P15)," "Increased accessibility to the areas with mobility issues (not well served by PT) (P20)" that, according to experts' opinion, may prove to be critical in fostering widespread adoption of shared electric mobility. It is clear from the results that the effective financial strategies coupled with optimally chosen locations for SEMS stations, and several infrastructure-oriented provisions can prove to be successful in uplifting the modal share of shared electric mobility.

5. Conclusions

Shared electric mobility, widely recognised as one of the sustainable means of transportation, integrates the benefits of different e-mobility modes, has the potential to mitigate negative externalities of extensive car-use. It can create more efficient and inclusive multimodal urban mobility system, thereby benefiting at environmental, economic, and societal levels. However, the current transport policy frameworks of most countries have limited provisions for shared mobility services. In order to foster the widespread utilization of shared electric mobility modes, this chapter offers a unique framework to understand and evaluate the associated barriers and potential policy implications. This study has applied holistic approach to ensure that most potential barriers to SEMS adoption are considered, providing thorough understanding of the challenges. An integrated two-phase multi-criteria decision-making (MCDM) method was employed for this purpose. The first phase consisted of finalising the initially derived list of barriers and policy solutions using a systematic Delphi-based analysis. The second phase of the methodology consisted of the fuzzy Best-Worst Method (BWM) to evaluate the weights of selected barriers and sub-barriers, followed by the fuzzy Combined Compromise Solution (CoCoSo) technique to rank the policy solutions. Sensitivity analysis results revealed the robustness of the achieved results in terms of the final ranks of the solutions. Lastly, policy interventions were discussed in-depth based on these findings that are useful for widespread adoption of SEMS.

The findings underscore the importance of addressing behavioural, policy, and infrastructural barriers to realise the full potential of shared electric mobility services. At this juncture, it is important to understand that addressing these challenges requires collective and coordinated efforts from federal- and local-level policy makers and service operators. Close coordination between operators and authorities ensures clear understandings of the market conditions and how the needs of service providers may align with authorities' priorities and targets. As the habit of using private vehicles is a key barrier to the uptake of SEMS, steps should be taken to improve the attractiveness of alternative transport modes that can create positive conditions for decreasing car-usage and increasing shared vehicle usage. The provisions for physical infrastructure, digital infrastructure and the integration with public modes of transport can elevate the benefits of using shared electric mobility. Our analysis showed that relying solely on private vehicles restriction policies such as congestion pricing cannot drive the shift from private cars to sustainable transport alternatives. Rather it is more important to develop and manage strong physical and charging infrastructure for safe and smooth travel particularly for micromobility modes; and for that, focusing on robust nationwide financial framework is imperative. Supportive policies that address social equity and increase accessibility in underserved areas (i.e., public transport coverage) can foster widespread adoption. The authors pose that the consumer-oriented mixed approach is required from government bodies and private operators for effective implementation and profitable operation of SEMS. All in all, the results offer practical insights to support decision-making in shared electric mobility.

Policymakers can utilise the proposed policy measures to formulate targeted interventions that address the most critical barriers first. For instance, prioritising systematic financial investments, infrastructural developments, and service-level integrations can significantly accelerate the adoption of EVSS. The research findings also have broader implications from urban mobility planning perspective. The proposed fuzzy-MCDM framework can be adapted to different regions and frame policies according to the local conditions.

Though our study results are country-specific, it can be applied to other countries/regions with suitable adjustments as they may face unique challenges and require tailored policy solutions. Though the Behavioural barriers were found to have the highest weightage, it is crucial to maintain balanced focus on other barriers as well. It is important to note that the weights of all experts in the evaluation process were kept equal changing in which looking to their positions could be reflected in the results as well. Although the experts were chosen based upon their expertise, their views might not fully represent the broader stakeholder community. As future directions, this exercise can be done including diverse community perspective that might enhance the robustness of the results. The different combinations of MCDM techniques enriched with different extensions of fuzzy sets, such as interval type-2, hesitant, Pythagorean, intuitionistic can be applied to check the robustness of the outcomes. It would also be interesting to analyse the interrelationship between sub-barriers, and individual impact of solutions on selected set of sub-barriers. The proposed methodology is pragmatic and flexible that can be applied to any complex multi-criteria decision-based problems involving uncertainty, aimed at selecting best alternative.

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Appendix to Chapter 2

Appendix 2.1. Some basic concepts of Trapezoidal fuzzy sets.

Definition 1 A given fuzzy number $\tilde{A}$ denoted as $\tilde{A} = (l, m, n, u)$ is defined as a trapezoidal fuzzy number is its membership function $\mu_{\tilde{A}}(x)$ is equal to

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & if\ x < l, \\ \dfrac{x-l}{m-l} & if\ l \le x \le m, \\ 1 & if\ m \le x \le n, \\ \dfrac{x-u}{n-u} & if\ n \le x \le u, \\ 0 & if\ x > u. \end{cases} \quad (2.1)$$

where $x \in R$, and l, m, n, u are real numbers with $l \le m \le n \le u$. The x in interval $[m, n]$ imparts the maximum value for $\mu_{\tilde{A}}(x)$ which is equal to 1, that is the most probable value in fuzzy evaluation. Further, l and u are the lower and upper limits of the fuzzy evaluation reflecting the fuzziness of the evaluation data. The α-cut interval for a given TrFN $\tilde{A}$ can be written as $\tilde{A}_\alpha = \left[(m-l)\alpha + l, -(u-n)\alpha + u\right]$. Figure A1 represents the geometry of trapezoidal fuzzy number and α-cuts.

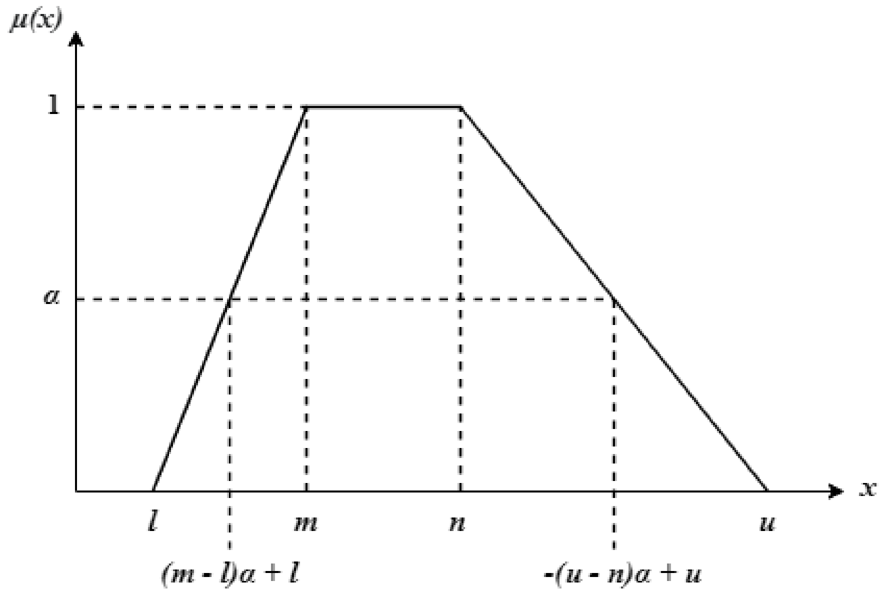

Figure 2.6 Geometric representation and α-cut for TrFN.

Definition 2 A finite and totally ordered linguistic terms set with an odd cardinal is defined as

$$S = \left(s_i \mid i = 0, 1, \ldots, (n/2)-1, n/2, (n/2)+1, \ldots, n\right). \quad (2.2)$$

where s_i is the (i + 1)th linguistic term and n is an even number and middle term represents 'neutral' with probability of 'approximately 0.5.' The remaining terms exhibit the following properties:

The set if ordered with comparison operation: $s_i \geq s_j,\ if\ i \geq j$.

The negotiation operation: $Neg(s_i) = s_j$ such that $j = n - i$.

The maximization operation: $\max(s_i,\ s_j) = s_i,\ if\ s_i \geq s_j$.

The minimization operation: $\min(s_i,\ s_j) = s_j,\ if\ s_i \geq s_j$.

Definition 3 Consider two trapezoidal fuzzy numbers $\tilde{A}_i = (l_i,\ m_i,\ n_i,\ u_i)$ and $\tilde{A}_j = (l_j,\ m_j,\ n_j,\ u_j)$. The addition of the two TrFNs can be performed as:

$$\tilde{A}_i + \tilde{A}_j = \left(l_i + l_j,\ m_i + m_j,\ n_i + n_j,\ u_i + u_j\right) \tag{2.3}$$

The product of the two TrFNs, being $\tilde{A}_{ij} = (l_{ij},\ m_{ij},\ n_{ij},\ u_{ij})$, can be approximated by the following formulas:

$$\begin{aligned}
l_{ij} &= \frac{3}{2}\left(m_i - l_i\right)\left(m_j - l_j\right) + 2\left[\left(m_i - l_i\right)l_j + \left(m_j - l_j\right)l_i\right] + 3l_i l_j - 2m_i m_j,\\
m_{ij} &= m_i m_j,\\
n_{ij} &= n_i n_j,\\
u_{ij} &= \frac{3}{2}\left(u_i - n_i\right)\left(u_j - n_j\right) + 2\left[\left(u_i - n_i\right)n_j + \left(u_j - n_j\right)n_i\right] + 3u_i u_j - 2n_i n_j.
\end{aligned} \tag{2.4}$$

Definition 4 For a given TrFN $\tilde{A} = (l, m, n, u)$, its defuzzification value, also termed as the graded mean integration representation (GMIR), can be obtained using following equation:

$$R\left(\tilde{A}\right) = \frac{l + 2m + 2n + u}{6} \tag{2.5}$$

Appendix 2.2. Steps followed in fuzzy-BWM approach.

Establish decision criteria system: it consists of constructing a set of decision criteria, which is important for evaluating alternatives at later stage. Let C be the set of n decision criteria such that, $C = \left\{c_i \mid i = 1(1)n\right\}$.

Choose the best criterion and the worst criterion: in this step, the decision maker is entitled to identify the best (most important) criterion $C_B \in C$ and the worst (least important) criterion $C_W \in C$.

Perform pairwise comparison: this step involves executing pairwise comparisons for the best and the worst criterion. By using the linguistic terms of importance, experts are asked to perform trapezoidal fuzzy pairwise comparison for both the criteria. Table 3 enlists the values of 5-point scale trapezoidal fuzzy spectrum used in this study.

Based on the linguistic evaluations of experts, the fuzzy preferences of the best criterion C_B over all other criteria can be determined and then can be transformed to TrFNs using the rules listed in Table 3. The resultant fuzzy Best-to-Others vector is formed as follows:

$$\tilde{V}_{Bi} = \left(\tilde{v}_{B1}, \tilde{v}_{B2}, ..., \tilde{v}_{Bn}\right). \tag{2.6}$$

where $\tilde{V}_{Bi}$ denotes fuzzy Best-to-Others vector, $\tilde{v}_{Bi}$ represents the fuzzy preference of the best criterion C_B over criterion $i\,(i = 1(1)n)$. It is to be noted that $\tilde{v}_{BB} = (1, 1, 1, 1)$.

In a similar way, the fuzzy preferences of all criteria over the worst criterion C_W can be determined using the linguistic evaluations performed by the experts. Then, the obtained fuzzy preferences can be transformed to TrFNs using the rules listed in Table 3. The resultant fuzzy Others-to-Worst vector can be obtained as:

$$\tilde{V}_{iW} = \left(\tilde{v}_{1W}, \tilde{v}_{2W}, ..., \tilde{v}_{nW}\right). \tag{2.7}$$

where $\tilde{V}_{iW}$ denotes fuzzy Others-to-Worst vector, $\tilde{v}_{iW}$ represents the fuzzy preference of criterion $i\,(i = 1(1)n)$ over the worst criterion C_W. It can also be known that $\tilde{v}_{WW} = (1, 1, 1, 1)$.

Determine the optimal fuzzy weights: this step involves estimating the weights of criteria using the constrained optimization problem formulation. Let $\left(\tilde{w}_1^*, \tilde{w}_2^*, ..., \tilde{w}_n^*\right)$ be the optimal fuzzy weights of the criteria $\left(c_1, c_2, ..., c_n\right)$.

For all criteria i, the optimal trapezoidal fuzzy weights should satisfy the equations:

$$\frac{\tilde{w}_B}{\tilde{w}_i} - \tilde{v}_{Bi} = 0$$

and

$$\frac{\tilde{w}_i}{\tilde{w}_W} - \tilde{v}_{iW} = 0$$

For this, it should determine the solution where the maximum absolute gaps $\left| \frac{\tilde{w}_B}{\tilde{w}_i} - \tilde{v}_{Bi} \right|$ and $\left| \frac{\tilde{w}_i}{\tilde{w}_W} - \tilde{v}_{iW} \right|$ for all i are minimized. Consider the trapezoidal fuzzy weight for criterion i as $\tilde{w}_i = (l_i^w, m_i^w, n_i^w, u_i^w)$. In this case, the problem can be formulated as below:

$$\min \max_i \left\{ \left| \frac{\tilde{w}_B}{\tilde{w}_i} - \tilde{v}_{Bi} \right|, \left| \frac{\tilde{w}_i}{\tilde{w}_W} - \tilde{v}_{iW} \right| \right\}$$

$$s.t. \begin{cases} \sum_{i=1}^{n} R(\tilde{w}_i) = 1 \\ l_i^w \le m_i^w \le n_i^w \le u_i^w \\ l_i^w \ge 0 \\ i = 1, 2, ..., n \end{cases} \tag{2.8}$$

Where $\tilde{w}_B = (l_B^w, m_B^w, n_B^w, u_B^w)$, $\tilde{w}_i = (l_i^w, m_i^w, n_i^w, u_i^w)$, $\tilde{w}_W = (l_W^w, m_W^w, n_W^w, u_W^w)$,

$\tilde{v}_{Bi} = (l_{Bi}, m_{Bi}, n_{Bi}, u_{Bi})$, $\tilde{v}_{iW} = (l_{iW}, m_{iW}, n_{iW}, u_{iW})$.

Next, Equation 2.8 can be rewritten as a following nonlinearly constrained optimization problem.

$$\min \ \tilde{\xi}$$

$$s.t. \begin{cases} \left| \frac{\tilde{w}_B}{\tilde{w}_i} - \tilde{v}_{Bi} \right| \le \tilde{\xi} \\ \left| \frac{\tilde{w}_i}{\tilde{w}_W} - \tilde{v}_{iW} \right| \le \tilde{\xi} \\ \sum_{i=1}^{n} R(\tilde{w}_i) = 1 \\ l_i^w \le m_i^w \le n_i^w \le u_i^w \\ l_i^w \ge 0 \\ i = 1, 2, ..., n \end{cases} \tag{2.9}$$

In which, $\tilde{\xi} = \left(l_{\tilde{\xi}}, m_{\tilde{\xi}}, n_{\tilde{\xi}}, u_{\tilde{\xi}} \right)$.

Considering $l_{\tilde{\xi}} \le m_{\tilde{\xi}} \le n_{\tilde{\xi}} \le u_{\tilde{\xi}}$, suppose $\tilde{\xi}^* = (k^*, k^*, k^*, k^*)$. Then Equation 2.9 can be transformed as follows:

$$\min\ \tilde{\xi}^*$$

$$s.t.\begin{cases} \left| \dfrac{\left(l_B^w, m_B^w, n_B^w, u_B^w\right)}{\left(l_i^w, m_i^w, n_i^w, u_i^w\right)} - \left(l_{Bi}, m_{Bi}, n_{Bi}, u_{Bi}\right) \right| \le \left(k^*, k^*, k^*, k^*\right) \\ \left| \dfrac{\left(l_i^w, m_i^w, n_i^w, u_i^w\right)}{\left(l_W^w, m_W^w, n_W^w, u_W^w\right)} - \left(l_{iW}, m_{iW}, n_{iW}, u_{iW}\right) \right| \le \left(k^*, k^*, k^*, k^*\right) \\ \sum_{i=1}^{n} R\left(\tilde{w}_i\right) = 1 \\ l_i^w \le m_i^w \le n_i^w \le u_i^w \\ l_i^w \ge 0 \\ i = 1,\ 2,\ ...,\ n \end{cases} \tag{2.10}$$

By solving the Equation 2.10, the optimal trapezoidal fuzzy weights $(\tilde{w}_1^*,\ \tilde{w}_2^*,\ ...,\ \tilde{w}_n^*)$ can be obtained, where $\tilde{w}_i = (l_i^w,\ m_i^w,\ n_i^w,\ u_i^w)$.

Check the consistency degree of pairwise comparison: the results are more meaningful when assessed with the consistency ratio (CR). When $\tilde{v}_{Bi} \times \tilde{v}_{iW} = \tilde{v}_{BW}$, the pairwise comparison is fully consistent. The inconsistency of the fuzzy pairwise comparison will occur when $\tilde{v}_{Bi} \times \tilde{v}_{iW} >$ or $< \tilde{v}_{BW}$. The greatest inequality will reach in $\tilde{\xi}$ when both $\tilde{v}_{Bi}$ and $\tilde{v}_{iW}$ are equal to $\tilde{v}_{BW}$. Considering the occurrence of greatest inequality, we can obtain Equation 2.11, by interpreting $\left(\dfrac{\tilde{w}_B}{\tilde{w}_i}\right) \times \left(\dfrac{\tilde{w}_i}{\tilde{w}_W}\right) = \left(\dfrac{\tilde{w}_B}{\tilde{w}_W}\right)$ as follows:

$$\left(\tilde{v}_{Bi} - \tilde{\xi}\right) \times \left(\tilde{v}_{iW} - \tilde{\xi}\right) = \left(\tilde{v}_{BW} - \tilde{\xi}\right) \tag{2.11}$$

For the maximum fuzzy inconsistency, we have $\tilde{v}_{Bi} = \tilde{v}_{iW} = \tilde{v}_{BW}$. Hence, the Equation 2.11 can be transformed as:

$$\tilde{\xi}^2 - \left(1 + 2\tilde{v}_{BW}\right)\tilde{\xi} + \left(\tilde{v}_{BW}{}^2 - \tilde{v}_{BW}\right) = 0 \tag{2.12}$$

where $\tilde{\xi} = \left(l_{\tilde{\xi}},\ m_{\tilde{\xi}},\ n_{\tilde{\xi}},\ u_{\tilde{\xi}}\right)$, and $\tilde{v}_{BW} = \left(l_{BW},\ m_{BW},\ n_{BW},\ u_{BW}\right)$ which can have a maximum value of (8, 17/2, 9, 9) for trapezoidal fuzzy value (see Table 3). That means the maximum value of l_{BW}, m_{BW}, n_{BW} and u_{BW} cannot be greater than 9. Hence, calculating the consistency index (CI) using the upper boundary u_{BW}, the solution has a CI of 13.77, using the Equation 2.12. All other objects within $\tilde{v}_{BW}$ can use this CI to remain effectively consistent because the

CI corresponding to $\tilde{v}_{BW}$ is the largest for the interval $[l_{BW}, u_{BW}]$. Similar process can be done to obtain CI values for all the TrFNs tabulated in Table 3. Table 4 shows the obtained CI values.

Estimate crisp weights: finally, using the Equation 2.13, the obtained optimal fuzzy weights $(\tilde{w}_1^*, \tilde{w}_2^*, ..., \tilde{w}_n^*)$ can be converted into its crisp value:

$$R(\tilde{w}_i) = \frac{l_i^w + 2m_i^w + 2n_i^w + u_i^w}{6}, \quad \forall i = 1(1)n \tag{2.13}$$

Appendix 2.3. Computational procedure followed in fuzzy-CoCoSo approach.

Construct an initial decision matrix: the initial step, common to all MCDM methods, is to form a decision matrix $X = [x_{ij}]_{m \times n}$. The experts are invited to evaluate m alternatives (i.e., solutions $S = \{s_1, s_2, ..., s_m\}$) with respect to n evaluation criteria $C = \{c_1, c_2, ..., c_n\}$ using the linguistic terms illustrated in Table 5.

Covert into fuzzy decision matrix: this step involves transforming linguistic evaluations performed by the experts into the respective trapezoidal fuzzy numbers (referred to Table 5) and constructing a fuzzy decision matrix $[\tilde{X}]_{m\times n} = \left[\left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right)\right]_{m\times n}$ $(i = 1, 2, ..., m;\ j = 1, 2, ..., n)$. This can be represented as:

$$\tilde{X} = \begin{bmatrix} \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) & \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) & \cdots & \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) \\ \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) & \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) & \cdots & \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) & \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) & \cdots & \left(\tilde{x}_{ij}^l, \tilde{x}_{ij}^m, \tilde{x}_{ij}^n, \tilde{x}_{ij}^u\right) \end{bmatrix} \tag{2.14}$$

Normalizing decision matrix: this step normalizes the fuzzy decision matrix. The elements of the normalized fuzzy decision matrix $[\tilde{Z}]_{m\times n} = \left[\left(\tilde{z}_{ij}^l, \tilde{z}_{ij}^m, \tilde{z}_{ij}^n, \tilde{z}_{ij}^u\right)\right]_{m\times n}$ are determined as follows:

$$\left(\tilde{z}_{ij}^l, \tilde{z}_{ij}^m, \tilde{z}_{ij}^n, \tilde{z}_{ij}^u\right) = \begin{cases} \left(\dfrac{\tilde{x}_{ij}^l}{\max_i \tilde{x}_{ij}^u}, \dfrac{\tilde{x}_{ij}^m}{\max_i \tilde{x}_{ij}^u}, \dfrac{\tilde{x}_{ij}^n}{\max_i \tilde{x}_{ij}^u}, \dfrac{\tilde{x}_{ij}^u}{\max_i \tilde{x}_{ij}^u}\right), & \text{for Benefit-criteria} \\ \left(\dfrac{\min_i \tilde{x}_{ij}^l}{\tilde{x}_{ij}^u}, \dfrac{\min_i \tilde{x}_{ij}^l}{\tilde{x}_{ij}^n}, \dfrac{\min_i \tilde{x}_{ij}^l}{\tilde{x}_{ij}^m}, \dfrac{\min_i \tilde{x}_{ij}^l}{\tilde{x}_{ij}^l}\right), & \text{for Cost-criteria} \end{cases} \tag{2.15}$$

Calculating the values of the weighted sum *(SB_i)* and weighted product *(PB_i)*: these values are calculated for all the alternatives by employing fuzzy normalized weighted Bonferroni mean (NWBM) and fuzzy normalized weighted geometric Bonferroni mean (NWGBM) functions, respectively. The expressions are:

$$SB_i^{p,q} = \left(\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \frac{w_i w_j}{1-w_i} \tilde{z}_i^p \tilde{z}_j^q \right)^{\frac{1}{p+q}} = \left(\begin{array}{l} \left(\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \frac{w_i w_j}{1-w_i} \tilde{z}_i^{(l)p} \tilde{z}_j^{(l)q} \right), \\ \left(\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \frac{w_i w_j}{1-w_i} \tilde{z}_i^{(m)p} \tilde{z}_j^{(m)q} \right), \\ \left(\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \frac{w_i w_j}{1-w_i} \tilde{z}_i^{(n)p} \tilde{z}_j^{(n)q} \right), \\ \left(\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \frac{w_i w_j}{1-w_i} \tilde{z}_i^{(u)p} \tilde{z}_j^{(u)q} \right), \end{array} \right)^{\frac{1}{p+q}} \tag{2.16}$$

$$PB_i^{p,q} = \frac{1}{p+q} \left(\prod_{\substack{i,j=1 \\ i \neq j}}^{n} \left(p\tilde{z}_i + q\tilde{z}_j \right)^{\frac{w_i w_j}{1-w_i}} \right) = \left(\begin{array}{l} \frac{1}{p+q} \left(\prod_{\substack{i,j=1 \\ i \neq j}}^{n} \left(p\tilde{z}_i^{(l)} + q\tilde{z}_j^{(l)} \right)^{\frac{w_i w_j}{1-w_i}} \right), \\ \frac{1}{p+q} \left(\prod_{\substack{i,j=1 \\ i \neq j}}^{n} \left(p\tilde{z}_i^{(m)} + \tilde{z}_i^{(m)} \right)^{\frac{w_i w_j}{1-w_i}} \right), \\ \frac{1}{p+q} \left(\prod_{\substack{i,j=1 \\ i \neq j}}^{n} \left(p\tilde{z}_i^{(n)} + q\tilde{z}_i^{(n)} \right)^{\frac{w_i w_j}{1-w_i}} \right), \\ \frac{1}{p+q} \left(\prod_{\substack{i,j=1 \\ i \neq j}}^{n} \left(p\tilde{z}_i^{(u)} + q\tilde{z}_i^{(u)} \right)^{\frac{w_i w_j}{1-w_i}} \right), \end{array} \right) \tag{2.17}$$

where $p, q \geq 0$, $w_j (j = 1, 2, ..., n)$ represents the relative weights of criteria obtained using the fuzzy BWM, $w_j \in [0,1]$ and $\sum_j w_j = 1$. The parameters *p* and *q* represent stabilization parameters, and their changes can influence the prioritization of final results. For the initial solution, $p = q = 1$.

Estimating the alternatives' scores: there are three appraisal scoring strategies employed for each alternative to obtain their relative weights. Following are the equations:

$$k_{ia} = \frac{PB_i + SB_i}{\sum_{i=1}^{m}\left(PB_i + SB_i\right)} \tag{2.18}$$

$$k_{ib} = \frac{SB_i}{\min_i\left(SB_i\right)} + \frac{PB_i}{\min_i\left(PB_i\right)} \tag{2.19}$$

$$k_{ic} = \frac{\lambda SB_i + \left(1-\lambda\right)PB_i}{\lambda \max_i\left(SB_i\right) + \left(1-\lambda\right)\max_i\left(PB_i\right)}; \quad 0 \le \lambda \le 1 \tag{2.20}$$

$$k_i = \frac{1}{\left(k_{ia}\,k_{ib}\,k_{ic}\right)^3} + \frac{k_{ia} + k_{ib} + k_{ic}}{3} \tag{2.21}$$

Equation 2.18 represents the additive normalized significance of the NWBM and NWGBM functions. Equation 2.19 evaluates the sum of the relative scores of NWBM and NWGBM, while Equation 2.20 represents the trade-off significance of the alternative observed. The value of coefficient λ in Equation 2.20 takes the values $0 \le \lambda \le 1$. It expresses the flexibility and stability of the proposed fuzzy CoCoSo method. It is important to note that examining the influence of varied values of the coefficient $\lambda (0 \le \lambda \le 1)$ on the final results is inevitable to assure the robustness of the solution in MCDM problem. Ultimately, the final score of each alternative is estimated by applying these three strategies using the Equation 2.21. The higher the score k_i of an alternative, the better it is.

Appendix 2.4. Details of the participating experts.

Sr. No.	Industry type	Experience (Yrs.)	Post
Expert 1	Academic	5	Researcher
Expert 2	Academic	29	Full Professor
Expert 3	Academic	20	Full Professor
Expert 4	Academic	9	Researcher
Expert 5	Academic	8	Researcher
Expert 6	Academic & Public Sector	9	Lecturer and Senior Technician
Expert 7	Academic & Industry Association	6	Researcher
Expert 8	Academic	6	Associate Professor

Expert 9	Academic	25	Researcher
Expert 10	Industry Association	10	Project Officer
Expert 11	Local Municipal Authority	7	Principal Transport Planning Officer
Expert 12	Academic	5	Researcher

Chapter 3

Understanding individuals' intentions to use shared electric mobility using structural equation modelling approach

Abstract

The transition to sustainable transport is a critical element in addressing the global challenge of climate change, urban congestion, and environmental degradation. Among the well-established sustainable transportation strategies, shared mobility with electrification have emerged as a promising alternative. This study investigates the factors influencing behavioural intentions to adopt shared electric mobility services, employing an extended model that combines Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB) theories within the Structural Equation Modeling (SEM) framework. The study was conducted in the United Kingdom and 726 responses were collected. Key findings reveal that personal innovativeness, perceived usefulness, and social influence positively drive shared electric mobility adoption intentions, while scepticism, perceived risk, and habitual reliance on private vehicles act as significant barriers. Furthermore, habit of car-usage has positive impacts user' scepticism and perceived risk, and negative impact on perceived usefulness, underscoring the critical role of habit in shaping adoption behaviours. These results contribute to a deeper understanding of adoption dynamics, offering valuable insights for policymakers and service providers to better understand the travel mode choice behaviour and formulate interventions that promote shared electric mobility adoption.

Keywords: Behavioural intention; Mobility adoption; Shared electric mobility; Structural equation modeling; Technology acceptance model (TAM); Theory of planned behaviour (TPB)

1. Introduction

The transition to sustainable transport is a critical element in addressing the global challenge of climate change, urban congestion, and environmental degradation. The pursuit of sustainable transportation is confronted by a range of systematic challenges that stem from both technological and behavioural barriers. The transportation sector is one of the largest contributors to greenhouse gas emissions globally, accounting for nearly 24% of CO_2 emissions from fuel combustion (World Resources Institute, 2019). Despite considerable advancements in clean technology and increasing awareness of environmental issues, the reliance of private vehicles, particularly internal combustion engine (ICE) vehicles, remains dominant (Humpe et al., 2022; Pokharel et al., 2023). This is particularly problematic in urban settings, where car ownership and usage contribute heavily to traffic congestion, air pollution, and consumption of non-renewable resources. In addition to environmental concerns, rapid urbanization and growing demand for transportation is placing immense pressure on existing infrastructure. Many cities are struggling to keep up with the rapid pace of urbanization, leading to increased congestion, parking shortages, and longer commute times (Ecer et al., 2023). Existing public transport systems, although key component of sustainable mobility, are often underfunded or outdated, resulting in inefficiencies and a decline in user satisfaction (Allen et al., 2019; Börjesson and Rubensson, 2019; Soza-Parra et al., 2019). These trends counteract the sustainability objectives by perpetuating inefficient land use and contributing to sprawling, car-dependent cities (Glaeser and Kahn, 2004). Further, behavioural factors have proven to be formidable barriers to the transition toward sustainable transport systems. Individuals' strong preferences for private vehicle ownership, ingrained travel habits, and concerns regarding the reliability, convenience, and safety of alternative mobility options have hindered the shift to sustainable transportation modes. In this context, fostering widespread behavioural change toward sustainable transportation requires multifaceted aspects addressing psychological, social, and technological determinants of transportation choices.

Sustainable transportation solutions, including electric vehicles and shared mobility systems, have become an essential focal point for policymakers, urban planners, as well as researchers in pursuit of environmental sustainability and social welfare (Oeschger et al., 2020; Chapter 2). Among the well-established sustainable transportation strategies, shared mobility with electrification have emerged as a promising alternative. These include electric-car sharing, electric-bike sharing, and electric-scooter sharing programs, which have gained popularity in cities across the globe (Liao and Correia, 2022). It has the potential to democratise access to clean transport with affordable prices especially where the localities which – a) are not well served by public transport, and 2) include lower-income households which may otherwise be excluded from the EV market due to high upfront costs. The shared electric mobility systems combine the environmental benefits of electric vehicles with the flexibility and resource efficiency of shared mobility, leading to reduced carbon footprint of transportation activities (especially when charged using renewable energy sources), lower traffic congestion, and decreased demand for parking space (Fukushige et al., 2021a; Jie et al., 2021; Oehme et al., 2022; Zhou et al., 2023). However, despite the potential of shared electric mobility to alleviate environmental and urban mobility issues, adaption rates remain limited across different regions and populations (Bösehans et al., 2023a; Ren et al., 2024).

In the last decade, many developed and developing countries have actively taken various approaches to promote shared electric mobility as part of their broader strategies to achieve sustainability goals. These typically include a combination of financial incentives, regulatory support, infrastructure development, and public-private partnerships. For example, the UK government has put forward several initiatives such as Future of Transport programme, Gear Change strategy, supporting Mobility hubs, and exempting movements of shared vehicles in Clean Air Zones amongst others (Department for Transport, 2020). Though such initiatives and support from government are imperative for the success of such innovative transport modes, it is equally important to understand psychological and cognitive factors that drives the consumers' intentions to adopt them. Several theories have been proposed to examine consumer behavioural intentions and acceptance of emerging technologies, of which, the theory of planner behaviour (TPB, Ajzen, 1991) and the technology acceptance model (TAM, Davis, 1989) have been extensively applied in studies for this purpose. Despite their wide applications, there are several limitations of both these models. For instance, TPB does not account for external variables such as mood, past experience, or habit, and environmental or societal factors that may influence the behavioural intention and motivation (Najmi et al., 2023). While TAM primarily based upon the importance of perceived usefulness and perceived ease of use in evaluating users' behavioural intentions, it neglects the impacts of environment and social variables which also may influence users' decision-making (Majhi et al., 2024). Literature poses that none of them has consistently demonstrated superior explanatory power or predictive accuracy in behavioural studies (Chen et al., 2007). Previous studies (e.g., Cheng, 2019; Ignacio et al., 2019; Majhi et al., 2024; Wong et al., 2024) advocate that leveraging the advantage of both TPB and TAM can enhance the model explainability compared to applying them individually.

With the above background, the current study aims to analyse intentions to adopt shared electric vehicles using the combination of TAM and TPB approaches within the structural equation modelling (SEM) framework. As such, this research aims to add knowledge to the current literature by examining – a) the influence of factors associated with both TAM and TPB models on shared electric mobility adoption intentions, b) mediating and moderating effects of habit on intentions, c) impacts of vehicle ownership and other sociodemographic characteristics and, d) influence of psychometric variables such as environmental consciousness and personal innovativeness on user's decision-making process. The information extracted from the aforementioned analysis can be useful to planners, policymakers and operators who seek to increase the adoption rate of the shared electric mobility services.

2. Literature review

The adoption of shared electric mobility systems has garnered considerable attention in recent years, with many studies focusing on understanding user intentions and identifying the key factors that drive the shift towards sustainable transport modes. Previous research has investigated shared electric mobility adoption across a range of contexts, such as the impact of modal shift – where users transition from traditional transport options to shared electric alternatives (e.g., e-scooters, e-bikes, and e-cars) – and how such shifts affect overall transportation systems (Aguilera-García et al., 2020a; Asensio et al., 2022; Badia and Jenelius, 2023; Becker et al., 2020; Eccarius and Lu, 2020b; Hollingsworth et al., 2019; Jie et al., 2021; Jin et al., 2020; Li et al., 2023; Prieto et al., 2017; Samadzad et al., 2023; Zhou et al., 2023; Ziedan et al., 2021). Studies have also explored usage patterns and user characteristics, examining how personal traits like age, income, and education influence the adoption of shared electric vehicles (SEVs) across different user demographics (Bretones and Marquet, 2022; Guo and Zhang, 2021; Liao and Correia, 2022; Reck et al., 2021; Schaefers, 2013). In addition, researchers have analysed the role of the built environment and spatial configurations, highlighting how factors like urban density, public transport availability, and geographic characteristics impact the uptake of shared mobility services (Bretones and Marquet, 2022; Chicco and Diana, 2022; McKenzie, 2019; Sprei et al., 2019). Another prominent area of research has centred on accessibility and connectivity, specifically examining how shared electric mobility enhances users' ability to access public transport or reach final destinations in urban settings. These studies often emphasize the first-mile/last-mile solutions offered by shared mobility systems, which fill gaps in conventional public transport routes, making shared electric mobility a convenient and time-efficient option for users (Baek et al., 2021; Oeschger et al., 2025; Shaheen and Chan, 2016; van Kuijk et al., 2022; Zuniga-Garcia et al., 2022b). Moreover, researchers have investigated user intentions and potential deterrents to adoption, such as perceived risks, cost considerations, and technological uncertainty (Fitt and Curl, 2019; Kroesen and Chorus, 2020). All in all, these investigations have revealed several determinants of shared electric mobility adoption that frequently appear in the literature.

Key factors influencing adoption include price sensitivity and time efficiency, both of which are critical as users weigh the costs of shared electric mobility services against other transport modes (Biegańska et al., 2021; Bieliński and Ważna, 2020; Curtale and Liao, 2023a; Glavić et al., 2021; Kaplan et al., 2018; Nematchoua et al., 2020b; Yoon et al., 2017). The short distance travels and first-mile/last-mile utility of SEVs has been noted as a major driver of adoption, especially to/from public transport stations where users seek flexibility in reaching final destinations (Krauss et al., 2022; Liao and Correia, 2022; Oeschger et al., 2025; Shaheen and Chan, 2016; Zuniga-Garcia et al., 2022b). Environmental consciousness also plays a significant role, with many users motivated by environmental awareness and a desire to reduce their carbon footprint (Curtale et al., 2021a; Edel et al., 2021; Kaplan et al., 2018; Kopplin et al., 2021). The perceived risk and safety of SEVs, especially for micro-mobility modes like e-scooters and e-bikes, is another important determinant, as concerns over accident risks or road infrastructure quality often influence adoption decisions (Bateman et al., 2021b; Bieliński et al., 2020; Sellaouti et al., 2020). Other factors include the perceived usefulness and compatibility of shared electric mobility with an individual's lifestyle and transportation needs (Buehler et al., 2021; Mayer, 2020). Studies have shown that users who view SEVs as convenient and suitable for their travel routines are more likely to adopt these systems (Edge et al., 2018; Mitra and Hess, 2021). Social perception is also a major determinant, where the influence of peer behaviour and societal norms can significantly impact decisions to adopt shared electric mobility (Behrendt, 2018; Kaplan et al., 2018). Personal innovativeness, or the degree to which an individual is willing to embrace new technologies, has emerged as another key factor, with early adopters often being more open to experimenting with SEVs (Bösehans et al., 2023b; Kaplan et al., 2015). Furthermore, the presence of supportive infrastructure, such as charging stations, bike lanes, and designated parking zones, facilitates adoption by reducing practical barriers to using these services (Bobičić and Esztergár-Kiss, 2024; Bretones and Marquet, 2022; Tyrer and Orchard, 2021). Lastly, sociodemographic characteristics—including age, income, education, and vehicle ownership—have been shown to affect the likelihood of adopting shared mobility options, with younger, urban populations being more likely to engage in SEV usage (Aguilera-García et al., 2020a; Curtale et al., 2021b; Curtale and Liao, 2023a).

Despite the growing body of literature on the adoption of shared electric mobility, there is still room to understand the impact of users' perspectives on the usage of these services. Most studies focus primarily on technological and infrastructural factors, with less attention given to the psychological and habitual aspects of transportation choices. For instance, the role of habit (Moser et al., 2018; Rejeb et al., 2023), personal characteristics (Ramos et al., 2020), and overall satisfaction (Mouratidis et al., 2023; Xia et al., 2022) with existing transport modes. These factors likely play a critical role in shaping users' intentions and adoption patterns but have been underrepresented in the literature. Furthermore, much of the existing research has focused on free-floating shared mobility services, such as dockless e-scooter sharing and e-bike sharing, and free-floating e-carsharing. While these services offer flexibility, they require high and unsustainable operation costs to relocate vehicles to match variable demands (Wang and Liao, 2021). Till date, limited attention has been given to the concept of mobility hubs, i.e., station-based services. Shared mobility hubs, which are centralized locations that integrate multiple shared electric modes (often in dense neighbourhoods and at transit stations), offer distinct advantages by concentrating shared mobility options in specific, high-demand areas, enhancing accessibility and connectivity across transportation networks (Aydin et al., 2022; Bösehans et al., 2023b). The exploration of these hub-based services is still in its early stages, leaving a gap in understanding how they can further promote shared electric mobility adoption. Therefore, this study complements the existing literature by analysing the intentions to adopt station-based shared electric mobility services by employing key determinants from TAM and TPB models.

The next section will introduce the methodological framework, which includes conceptual model, proposed hypotheses, overview of the survey instruments and sample description. Section 4 will cover the analysis using structural equation modelling technique and obtained results. Section 5 will discuss the results and related policy implications, followed by the concluding remarks, study limitations and future work in Section 6.

3. Methodological framework

This section explains the overall study framework including the research model adopted and proposed hypotheses pertaining to the factors influencing the intentions to adopt shared electric mobility services. Besides, the data collection and data statistics are also discussed in detail.

3.1. Conceptual model

As described earlier, this study uses the underlying concepts of TAM and TPB models to analyse users' intentions to use shared electric mobility services. These models pose that the intention to use/adopt a service/technology has the direct effect on the behaviour. Further, such theories require some level of understanding or use experience of the concerned technology, which may otherwise lead to the biased results. Hence, looking to the current establishments of the shared electric mobility services including e-cars, e-bikes, and e-scooters around the cities, and current understanding of the adoption intentions in literature, a conceptual model is developed as presented in the Figure 3.1. Besides, Table 3.1 describes the latent variables proposed in this study.

Table 3.1 Description of the latent variables.

Variable	Description	Source
Personal Innovativeness (PI)	The degree to which respondents tend to adopt new technologies, services, or products, earlier than others.	(Bösehans et al., 2023b; Flores and Jansson, 2021a; Kaplan et al., 2015)
Environmental Awareness (EA)	The degree to which respondents concern about the environmental impacts of their daily travel behaviour.	(Edel et al., 2021; Kaplan et al., 2018; Kopplin et al., 2021)
Social Influence (SI)	The degree to which respondents feel that people known to them believe that they should use SEVs.	(Behrendt, 2018; Kaplan et al., 2018; Leger et al., 2019)
Scepticism (SC)	The degree to which respondents are reluctant to adopt SEVs relative to their personal vehicle usage.	New construct based on (Trieste and Turchetti, 2024)
Perceived Risk (PR)	The degree to which respondents perceive the risk (be it financial, physical, psychological or time) in adoption of shared electric mobility.	New construct based on (Bateman et al., 2021b; Bieliński and Ważna, 2020; Sellaouti et al., 2020)
Perceived Usefulness (PU)	The degree to which respondents believe that using SEVs is beneficial to their travel.	(Buehler et al., 2021; Mayer, 2020)
Mode-use Habit (HAB)	The tendency of respondents to automatically choose the mode of daily transport based on well-learned associations between cues and behaviours.	(Klöckner and Matthies, 2004; Moser et al., 2018; Verplanken and Orbell, 2003)

Intention to adopt (IA)	The degree to which respondents intend to adopt the shared electric mobility.	-

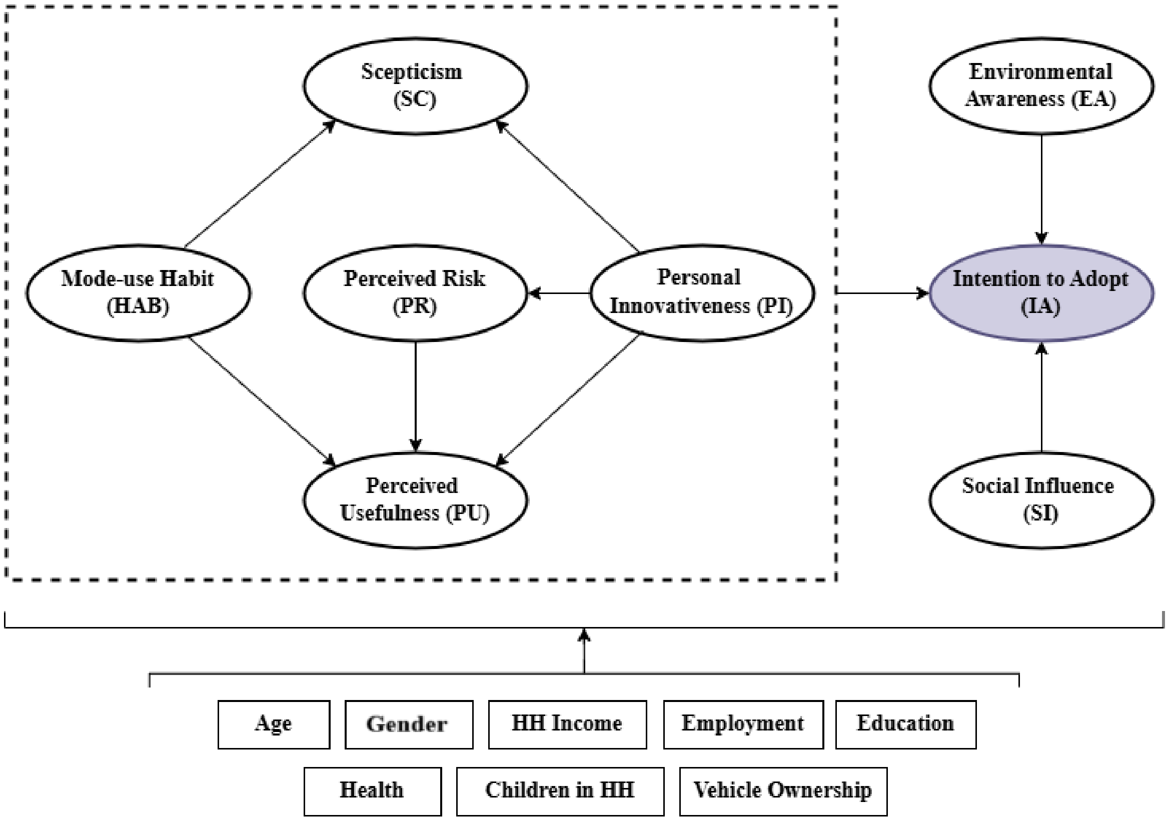

Figure 3.1 Conceptual framework.

This study assumes that the latent variables, namely, personal innovativeness, scepticism, perceived risk, perceived usefulness, social influence (also termed as social norm), and environmental awareness have direct influence on the behavioural intention to adopted shared electric mobility. Additionally, habit (of using private vehicle) is supposed to directly and indirectly impact the consumers' intention. Several individual level characteristics (see Figure 1) are also considered to examine their direct and moderating effects on latent variables and relationships between latent variables respectively. The key hypothesis proposed in this study are as follows:

a) Latent variables affecting behavioural intention:

H1: Personal innovativeness has positive impact on consumers' intention.
H2: Perceived usefulness has positive impact on consumers' intention.
H3: Environmental awareness has positive impact on consumers' intention.
H4: Social influence (positive) has positive impact on consumers' intention.
H5: Perceived risk has negative impact on consumers' intention.
H6: Scepticism has negative impact on consumers' intention.
H7: Habit has negative impact on consumers' intention.

b) Latent variables affecting other latent variables:

H8: Habit has positive impact on Scepticism and Perceived risk, and negative impact on Perceived usefulness.

H9: Personal innovativeness has negative impact on Scepticism and Perceived risk, and positive impact on Perceived usefulness.

H10: Perceived risk has negative impact on Perceived usefulness.

c) Effects of personal characteristics:

H11: Personal characteristics have direct impact on consumers' intention. (e.g., females and elder people may have weak intentions.)

H12: Personal characteristics have moderating effect on relationship between latent variables and consumers' intention. (e.g., higher education can enhance the positive relationship between Personal innovativeness and consumers' intention.)

3.2. Survey and data collection

A web-based questionnaire survey was designed based on the conceptual framework presented in Figure 3.1. At the beginning of the survey, participants were presented with a brief explanation of the station-based shared electric mobility services using text and figure. In the first part of the survey, participants were asked to declare their level of agreement on each psychometric statements on a 5-point Likert's scale ranging from 1 = "totally disagree" to 5 = "totally agree" with middle point 3 = "neutral". A total 25 psychometric statements were evaluated on a 5-point Likert's scale to measure seven latent constructs (see Table 3.2). To measure the intention to adopt shared electric mobility, phrases such as, "I intend to...", "I am willing to...", "It is possible for me to use...", "It can be my first choice..." were operationalised in the questionnaire. The mode-use habit can be evaluated using either frequency-based measures or automaticity-based features. This study adopted the second approach which is posited as more reliable than mere frequency counting (Gardner, 2012; Gardner et al., 2012). The measurement items used this study for habit were based on the 12-item Self-Report index of habit strength (Gardner et al., 2012; Verplanken and Orbell, 2003). The latent construct of mode-use habit is composed of five items on same 5-point Likert's scale as mentioned earlier. These items are reflective of the respondents' habitual mode choice which they tend to make without deliberate thinking and keeps them free and relaxed (refer to Table 3.2). Lastly, sociodemographic and travel-related characteristics such as age, gender, occupation (employment), household income, level of education, and vehicle ownership (car, motorbike, bicycle, e-bike, e-scooter) were collected through multiple-choice questions.

Table 3.2 Measurement items.

Construct	Code	Item
Personal Innovativeness (PI)	PI1	I would be interested in trying innovative ways to travel.
	PI2	It's easy to handle and use these new generations of vehicles.
	PI3	I always enjoy adopting new technologies in my regular life.
Environmental Awareness (EA)	EA1	Shared e-mobility has the potential to reduce urban traffic congestion.
	EA2	I believe that shared e-mobility can help protect the environment.
	EA3	I believe that people should avoid using private vehicles unless extremely necessary.
Social Influence (SI)	SI1	I would wait for my peers to use new shared services before I use them.
	SI2	Using it makes a good impression, and I can set an example to my peers.
	SI3	In my view, shared e-mobility users are perceived in a positive manner.
Scepticism (SC)	SC1	Using a car allows me to do whatever I want and not to think much about other factors.
	SC2	I own a car and can afford it, no point in using other modes.
	SC3	I do not like to walk much during my commuting trips.
Perceived Risk (PR)	PR1	I do not think it is safe to use shared electric services.
	PR2	I doubt the reliability of these electric vehicles.
	PR3	I doubt the cleanliness and maintenance of the shared vehicles.
Perceived Usefulness (PU)	PU1	I believe that shared mobility can provide me with more flexibility in travel.
	PU2	Shared mobility would be suitable for work trips.
	PU3	Using it, I can save on vehicle ownership and maintenance costs.
	PU4	I think that these e-micromobility are perfect options to supplement my public transit trips
	PU5	I see this system as a health tool as I will be more physically active while accessing/travelling with it.
Mode-use Habit (HAB)	HAB1	I usually choose car/PT for my usual trips without thinking too much.
	HAB2	Travelling by car/PT is part of my daily life.
	HAB3	I feel free and relaxed while travelling with car/PT.
	HAB4	It's been a long time since I travelled without car/PT.
	HAB5	It's very difficult for me to stop using car/PT.
Intention to adopt (IA)	IA1	I intend to use shared electric mobility in the near future.
	IA2	I am willing to use shared electric mobility in the near future.
	IA3	It is possible for me to use shared electric mobility if I have access to it.
	IA4	Shared electric mobility would be my first choice of travel for commuting.

3.3. Sample description

The survey was administered in the England during July/August 2024 after pretesting of the survey in May 2024. Several cities including, Birmingham, Manchester, Liverpool, Leeds, Nottingham, and Sheffield were selected for this study. These cities exhibit comparable demographics, transport infrastructure including availability of shared electric mobility services, economic profile, and car-dominant commute which makes it suitable to operationalise aggregated behavioural data to investigate travellers' intentions to adopt SEVs. Participants were recruited using an online panel for market research which allowed for control in terms of sample representativeness. The target population includes the adults (over 18 years of age) who possess driving license, living in one of the selected cities, commute at least 2 days a week within the city limits to ensure that the participants can pick-up/drop-off and travel using SEVs for their commute journey. After screening off the ineligible participants and removing unengaged/poorly-attended samples, 726 observations were considered for the further analysis.

Table 3.3 summarises the descriptive statistics of sociodemographic variables for the final sub-sample. The sub-sample is slightly overrepresented by the females (55.8%) and underrepresented by the males (44.2%) compared to the UK national average (female proportion of ~51%). The largest age group falls between 25-34 years (34.16%), followed by 35-44 years (27.1%), with only 1.38% of respondents being older than 65 years. Education levels show a high representation of undergraduates (46.3%) and postgraduates (24.7%), which reveals high biasedness towards higher qualified respondents. Employment status indicates that most participants are full-time workers (67.2%), while part-time workers account for 24.1%. With higher percentage of full-time working and highly qualified respondents, more than 60% of them having household income greater than £40,000, while only slight proportion of the respondents (5.9%) earn lesser than £20,000. Household demographics show that 52.9% have two adults, 21.5% have three adults, and 47.2% have children, which are somewhat near to the UK census. Car ownership is common, with 95% of households owning at least one car, while bicycle ownership is slightly less prevalent, with 38.84% owning none. Health satisfaction, measured on a 10-point scale (with 10 being extremely satisfied), averages 7.31 (SD = 1.79), suggesting a generally positive self-assessment.

Table 3.3 Descriptive statistics of the survey participants (N=726).

Characteristics	**Levels**	**Frequency**	**Proportion (%)**
Gender	Female	405	55.79%
	Male	321	44.21%
Age	18-24	70	9.64%
	25-34	248	34.16%
	35-44	197	27.13%
	45-54	133	18.32%
	55-64	68	9.37%

	65 and older	10	1.38%
Education level	Primary School	0	0.00%
	Secondary School	183	25.21%
	Undergraduation	336	46.28%
	Postgraduation	179	24.66%
	Professional qualification	28	3.86%
Employment	Full-time worker	488	67.22%
	Part-time worker	175	24.10%
	Self-employed	42	5.79%
	Business	2	0.28%
	Student	19	2.62%
Income level (yearly)	< £20,000	43	5.92%
	£20,000 - £39,999	230	31.68%
	£40,000 - £59,999	156	21.49%
	£60,000 - £79,999	150	20.66%
	£80,000 - £99,999	108	14.88%
	> £100,000	39	5.37%
Adults in household	One	94	12.95%
	Two	384	52.89%
	Three	156	21.49%
	Four or more	92	12.67%
Children in household	Yes	343	47.25%
	No	383	52.75%
Number of cars	Zero	33	4.55%
	One	363	50.00%
	Two	288	39.67%
	Three or more	42	5.79%
Number of bicycles	Zero	282	38.84%
	One	219	30.17%
	Two	124	17.08%
	Three or more	101	13.91%
Satisfaction with health	On 10-point scale	**Mean (SD)**	7.31 (1.79)

3.4. Method

A structural equation modelling (SEM) approach is well-suited to analyse the inter-relationships amongst latent variables through the systematic set of measurement and structural models (Ullman and Bentler, 2012). Within the SEM framework, multiple regression models are analysed to test the impact of various latent factors and other explanatory variables on the behavioural intention. Firstly, the underlying latent constructs were extracted based on selected measurement variables using an exploratory factor analysis (EFA). Subsequently, the confirmatory factor analysis (CFA) was performed along with several tests for internal consistency, convergent and discriminant validity, multicollinearity, and composite reliability to confirm the factor structure obtained through EFA. Lastly, a covariance-based SEM (CB-SEM) model was estimated to test the proposed hypotheses according to the conceptual model presented in Figure 1. Please note that all the underlying interrelationships between latent constructs (i.e., path analysis) and confirmatory factor analysis were estimated simultaneously in the final SEM model. These steps are discussed in detail in the next section. All the analyses in this study were performed in R environment using lavaan package (Rosseel et al., 2019) and semTools package (Jorgensen et al., 2019).

4. Data analysis

Before operationalising EFA, all the measurement items were tested to confirm their heterogeneity and asymmetricity through descriptive analysis (refer to Appendix A1). The average rating for the measurement item is slightly above three and most standard deviations are near or above one, indicating heterogeneity in respondents' ratings. Most of the measurement items show a positive kurtosis and skewness different from zero which signifies the asymmetricity in the data. Therefore, it is feasible to adopt these data for further analysis.

4.1. EFA

At first, preliminary EFA was performed to analyse the relationships between measurement items (which are discrete variables measured with Likert scale) and the latent factors and validate the derived latent constructs. It was observed that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity present values 0.90 and $p < 0.001$ respectively testifying the adequacy of performing EFA on the data under consideration (Dziuban and Shirkey, 1974). Table 3.4 presents the summary of the EFA results of the eights constructs explaining 66.82% of the total variability in the measurement items. Factor loadings of all the items in the final pattern matrix exceed the threshold value of 0.50 and remain highest on the expected latent variable and hence included for the subsequent analysis. In terms of convergent validity, the correlation values of the measurement items within the extracted factors remain above 0.4, implying higher interrelations between them. In order to ensure the discriminant validity, this study has utilized Hetotrait-monotrait (HTMT) criterion that compares the average correlations of indicators across constructs (heterotrait-heteromethod correlations) with the average correlations within constructs (monotrait-heteromethod correlations) (Henseler et al., 2015). This method is proven as highly sensitive and more robust compared to traditionally used methods such as the Fornell-Larcker criterion and the assessment of cross-loadings (Henseler et al., 2015). Table 3.5 shows the HTMT correlations between the extracted latent factors. All the correlation values between factors are lesser than 0.85, suggesting that they are fundamentally distinct and confirm the discriminant validity of the model.

Table 3.4 Results of exploratory factor analysis.

Items	Latent factors							
	PI	**EA**	**SI**	**SC**	**PR**	**PU**	**HAB**	**IA**
PI1	0.875							
PI2	0.652							
PI3	0.655							
EA1		0.699						
EA2		0.668						
EA3		0.706						
SI1			0.670					
SI2			0.557					
SI3			**0.324**					
SC1				0.543				
SC2				0.771				
SC3				0.505				
PR1					0.666			
PR2					0.610			
PR3					0.670			
PU1						0.824		
PU2						0.627		
PU3						0.569		
PU4						0.705		
PU5						0.682		
HAB1							0.705	
HAB2							0.754	
HAB3							0.651	
HAB4							0.606	
HAB5							0.819	
IA1								0.769
IA2								0.795
IA3								0.736
IA4								0.705
Cronbach's alpha	0.778	0.751	0.714	0.605	0.732	0.838	0.822	0.912

Table 3.5 HTMT correlation values of latent variables.

	PI	**EA**	**SI**	**SC**	**PR**	**PU**	**HAB**	**IA**
PI								
EA	0.382							
SI	0.471	0.390						

SC	0.755	0.457	0.183				
PR	0.554	0.238	0.242	0.820			
PU	0.580	0.328	0.474	0.578	0.690		
HAB	0.143	0.720	0.142	0.249	0.210	0.100	
IA	0.802	0.410	0.364	0.854	0.716	0.635	0.275

4.2. CFA

Confirmatory factor analysis (CFA), also known as measurement model in SEM, was subsequently conducted to confirm the factor structure obtained through EFA. Since the data used in this study is measured on 5-point Likert scale, they deemed to be ordinal in nature and does not necessarily follow a normal distribution. Therefore, the Diagonally Weighted Least Squares (DWLS) method adjusted for Mean and Variance (collectively termed as WLSMV) was chosen over traditional Maximum Likelihood (ML) estimation method (Li, 2014). Table 3.6 displays the results of CFA. In order to maintain factor loadings >0.5 for all the items, an indicator SI3 was removed which resulted in higher alpha and CR values for the latent construct SI. The Cronbach's alpha values for all the resulting factors are within acceptable limits (Taber, 2018), which indicate the internal consistency of the latent constructs. The average variance extracted (AVE) > 0.5 for all the latent factors signifies the convergent validity of the model. The composite reliability (CR) is supported by the values of greater than 0.6. Further, several model fit indices were employed to empirically evaluate the quality of the proposed measurement models. A chi-square test $\chi^2(322) = 1568.55$ with $p < 0.01$, the Root Mean Square Error of Approximation (RMSEA) value of 0.073, the comparative fit index (CFI) = 0.978, the Tucker-Lewis Index (TLI) = 0.974, Standardized Root Mean Square Residual (SRMR) value of 0.069 indicate that the model fits the data with satisfactory goodness-of-fit measures (Hu and Bentler, 1999; Kaplan, 2009). Hence, the derived latent factors can be exercised in SEM.

Table 3.6 Results of confirmatory factor analysis.

Construct	**Items**	**Factor loadings**	**Cronbach's alpha**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Personal Innovativeness (PI)	PI1	0.908	0.778	0.755	0.565
	PI2	0.654			
	PI3	0.667			
Environmental Awareness (EA)	EA1	0.818	0.751	0.839	0.602
	EA2	0.800			
	EA3	0.705			
Social Influence (SI)	SI1	0.788	0.714	0.677	0.558
	SI2	0.705			
	SI3	**dropped**			
Scepticism (SC)	SC1	0.589	0.615	0.601	0.498
	SC2	0.793			

	SC3	0.511			
Perceived Risk (PR)	PR1	0.729	0.732	0.689	0.579
	PR2	0.746			
	PR3	0.594			
Perceived Usefulness (PU)	PU1	0.785	0.838	0.820	0.520
	PU2	0.657			
	PU3	0.614			
	PU4	0.844			
	PU5	0.684			
Mode-use Habit (HAB)	HAB1	0.829	0.822	0.780	0.512
	HAB2	0.767			
	HAB3	0.681			
	HAB4	0.679			
	HAB5	0.778			
Intention to adopt (IA)	IA1	0.864	0.912	0.895	0.731
	IA2	0.917			
	IA3	0.825			
	IA4	0.810			

4.3. SEM model

Covariance-Based Structural Equation Modeling (CB-SEM) is a multivariate statistical technique that simultaneously estimates complex relationships between observed and latent variables. By optimizing the discrepancy between the sample and model-implied covariance matrices, CB-SEM provides rigorous evaluation of model fit, causal pathways, and measurement reliability, making it a robust tool for testing theoretical frameworks. After testifying the model's qualitative measures, SEM analysis was conducted on the derived latent constructs as well as other exogeneous variables (i.e., sociodemographic and travel characteristics). A bootstrapping method with 5000 draws at 95% confidence interval was employed to scrutinize the estimated structural model. The regression results with structural relationships directing toward intention to adopt (IA), i.e. hypotheses H1–H7 and H11, as well as interrelationships between the latent variables (hypotheses H8–H10) are reported in Table 3.7. The estimated SEM model with selected variables can explain up to 86.3% of the variability in IA. The results show that all seven latent variables have a significant relationship with the IA. Latent variables PI (β=1.977), EA (β=0.205), SI (β=0.328), and PU (β=0.514) have a positive influence on the IA, while SC (β=–0.226), PR (β=–0.204), and HAB (β=–0.396) have negative influence on the IA. It is seen that PI has the strongest direct effect on the IA with the highest path coefficient, while EA and PR clearly have comparatively smaller effects. These results hold the proposed hypotheses H1–H7 with expected direction.

Table 3.7 Regression results of SEM analysis.

Path	Std Estimate	Std Error	t-stat	p-value	95% CI LB	95% CI UB
PI → IA	1.977	0.713	2.774	0.006	0.580	3.374
EA → IA	0.205	0.121	1.695	0.090	-0.032	0.442
SI → IA	0.328	0.090	3.658	0.000	0.152	0.503
SC → IA	-0.226	0.108	2.080	0.038	-0.438	-0.013
PR → IA	-0.204	0.086	2.380	0.018	-0.372	-0.036
PU → IA	0.514	0.052	9.877	0.000	0.412	0.616
HAB → IA	-0.396	0.161	2.449	0.014	-0.712	-0.079
Age → IA	-0.104	0.077	1.348	0.178	-0.254	0.047
Female → IA	-0.960	0.214	4.494	0.000	-1.378	-0.541
Education → IA	0.314	0.134	2.349	0.019	0.052	0.576
HH Income → IA	-0.173	0.095	1.823	0.069	-0.359	0.013
Children in HH → IA	-0.422	0.218	1.932	0.054	-0.849	0.006
Car Ownership → IA	-0.709	0.211	3.357	0.001	-1.123	-0.295
Bicycle Ownership → IA	0.052	0.119	0.436	0.663	-0.182	0.286
Health Satisfaction → IA	0.115	0.058	1.995	0.046	0.002	0.228
HAB → SC	0.628	0.177	3.557	0.000	0.282	0.974
HAB → PU	-0.363	0.118	3.069	0.002	-0.594	-0.131
HAB → PR	0.056	0.008	7.317	0.000	0.041	0.071
PI → SC	-0.490	0.064	7.706	0.000	-0.614	-0.365
PI → PU	3.227	0.670	4.813	0.000	1.913	4.541
PI → PR	-0.513	0.052	9.955	0.000	-0.614	-0.412
PR → PU	-0.996	0.257	3.868	0.000	-1.500	-0.491
SC → HAB	0.252	0.099	2.533	0.011	0.057	0.447

Model statistics:
$\chi2(938) = 2661.269$ with $p < 0.001$; CFI = 0.949; TLI = 0.964; RMSEA = 0.050 with 90% CI [0.048, 0.053]; SRMR = 0.068.
$R^2 = 0.892$ (IA), $R^2 = 0.407$ (HAB), $R^2 = 0.895$ (PU), $R^2 = 0.242$ (PR), $R^2 = 0.647$ (SC).

Looking to the interrelationships between the latent constructs, HAB significantly affects SC (β=0.628), PU (β=–0.363), and PR (β=0.056), though the strength of the relationship HAB → PR is not much higher. These results are consistent with the proposed hypothesis H8. These relationships highlight that entrenched habits shape perceptions of shared mobility's feasibility, utility, and risks, indirectly influencing IA. Further, personal innovativeness (PI) shows strong relationship with SC (β=–0.490), PU (β=3.227), and PR (β=–0.513), demonstrating its role as a key driver of attitudes that ultimately impact IA, and indicating the acceptance of hypothesis H9. Perceived risk (PR) has a significant negative direct effect on PU (β=–0.996), which implies that hypothesis H10 is supported. Additionally, SC was found to have a significant positive influence on HAB (β=0.252), which indicates possible reciprocal (two-way) relationship between the two latent variables within the model. On other words, habitual respondents may lead to increased scepticism towards other travel modes, which in turn can further strengthen the habit of using the same travel mode. All these relationships may exhibit indirect impact on the IA, which is explored ahead in this section through mediation analysis.

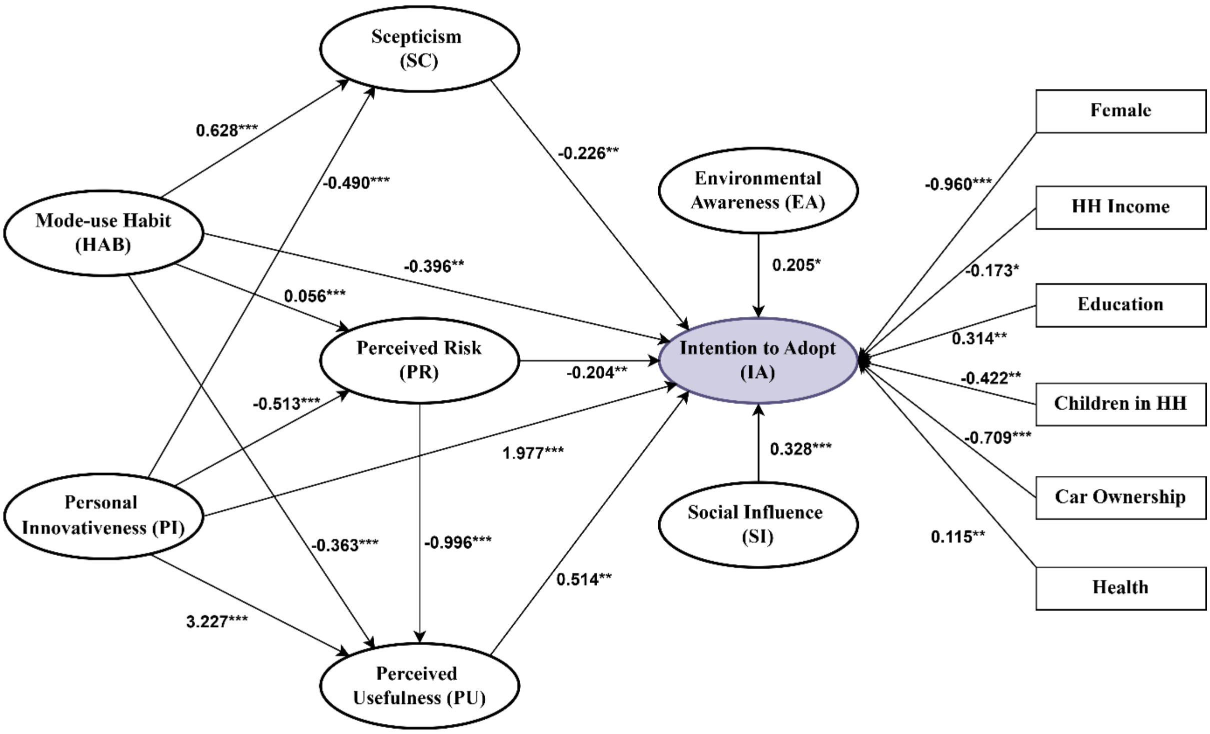

Figure 3.2 Graphical representation of the SEM model.
(***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10)

The results of the proposed model show that the effect of age is non-significant (β=–0.104, p=0.178), indicating a possibility of consistent interest towards shared electric mobility across different age groups. A strong significant Female → IA relationship implies that females are less likely to adopt shared electric mobility (β=–0.960). Education positively influences IA (β=0.314), which shows that respondents with higher educational attainment are more likely to adopt SEVs. Income has a marginally negative effect on the IA (β=–0.173), suggesting that higher-income group people may prefer private vehicles over shared ones. Further, the presence of children in the household also negatively affects IA (β=–0.422), possibly due to the convenience issues. Car ownership strongly and negatively associated with IA (β=–0.709), which underscores the competitiveness of private car ownership against shared mobility, though the bicycle ownership does not significantly influence IA. Health satisfaction positively influences IA (β=0.115), which implies that individuals who are content with their health condition may perceive shared mobility as a feasible and less physically demanding option. Figure 3.2 graphically portrays all the significant effects from the derived SEM model. Table 3.8 reports only significant effects of sociodemographic variables found on the derived latent constructs.

Table 3.8 Direct effects of sociodemographic variables on latent constructs.

Path	Std Estimate	Std Error	t-stat	p-value	95% CI LB	95% CI UB
Female → HAB	0.338	0.099	3.415	0.001	0.144	0.532
FTW → HAB	0.115	0.067	1.720	0.086	-0.016	0.245
Car Ownership → HAB	0.233	0.083	2.819	0.005	0.071	0.395
Female → PR	0.375	0.097	3.853	0.000	0.184	0.565
Age → PR	0.188	0.059	3.155	0.002	0.071	0.304
Education → PR	-0.349	0.134	2.611	0.009	-0.611	-0.087
Car Ownership → SC	0.804	0.140	5.751	0.000	0.530	1.078
HH Income → SC	0.130	0.058	2.255	0.024	0.017	0.243

4.4. Mediation and moderation analysis

Apart from identifying the direct relationships between latent constructs and IA, this study explored several possible and logical configurations for the mediation analysis. The approach proposed by (Baron and Kenny, 1986) was utilised to testify the mediation effects. Table 3.9 summarises the direct, indirect, and total effects on IA through given mediators. The authors did not find any full mediation effects. However, for both HAB → IA and PI → IA, all the effects are found significant through mediators SC and PU. This indicates that both SC and PU partially mediate the effects of HAB and PI on the IA. Perceived risk (PR) does not mediate the effects of HAB and PI towards IA as the respective indirect effects are not significant. In case of PR → IA, it is observed that PU partially mediates the negative association between PR and IA.

Table 3.9 Mediation effects of latent variables.

Path	Direct Effect	Indirect Effect	Total Effect	Comment
HAB → SC → IA	-0.395^{***}	0.142^{**}	-0.253^{**}	Partial Mediation
HAB → PU → IA	-0.395^{***}	-0.046^{***}	-0.441^{***}	Partial Mediation
HAB → PR → IA	-0.395^{***}	0.010	-0.385^{**}	No Mediation
PI → SC → IA	1.977^{***}	-0.110^{*}	1.867^{***}	Partial Mediation
PI → PU → IA	1.977^{***}	0.407^{*}	2.384^{***}	Partial Mediation
PI → PR → IA	1.977^{***}	-0.096	1.881^{***}	No Mediation
PR → PU → IA	-0.204^{**}	-0.512^{*}	-0.716^{***}	Partial Mediation

(***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10).

Further, the moderating effects of several demographic variables have been investigated by employing the interaction terms as illustrated in first column of the Table 3.10. The positive coefficients of moderating effects of gender(female) on PR → IA and SC → IA suggest that being a female further strengthens these negative relationships, i.e., females exhibit higher perceived risk and scepticism towards the IA. Having a higher level of education reinforces the positive relationship between PI and IA. Though age has no direct significant influence on IA

(Table 3.7), it significantly weakens the association between PI and IA, which means the higher the age, the lesser the innovativeness and so the intentions. Lastly, the authors have created a dummy variable of employment for full-time worker (FTW) to test its effect on the IA. The results show that FTW significantly weakens the relationship between PU and IA.

Table 3.10 Moderating effects of sociodemographic variables.

Path	Std Estimate	Std Error	t-stat	95% CI LB	95% CI UB	p-value
Female × PR → IA	0.028	0.007	3.717	0.013	0.042	0.000
Female × SC → IA	0.229	0.097	2.362	0.039	0.419	0.018
Education × PI → IA	0.237	0.060	3.937	0.119	0.355	0.000
Age × PI → IA	-0.466	0.142	3.276	-0.744	-0.187	0.001
FTW × PU → IA	-0.193	0.079	2.426	-0.348	-0.037	0.015

5. Discussion

This section synthesizes the results obtained using combined TAM-TPB models, discusses their implications, and proposed targeted policy measures to address barriers and enhance adoption.

5.1. Psychological factors

According to the results, personal innovativeness (PI) emerged as the strongest positive determinant of SEV adoption intentions. Besides, PI has a significant negative influence on the scepticism and perceived risk, whereas strong positive influence on perceived usefulness. This underscores the role of individuals openness to new ideas and technologies in driving early adoption. Highly innovative individuals are more likely to perceive SEVs as viable, useful and less-risky alternatives, resonating with prior research on technology adoption behaviour (Ciftci et al., 2021; Koivisto et al., 2016; Turan et al., 2015). The significant positive influence of perceived usefulness (PU) highlights the importance of SEVs' functional benefits, such as convenience, cost savings, and flexibility perceived amongst the positive adopters. These findings align with studies that emphasize the role of perceived utility in shared mobility adoption, reinforcing the need to highlight practical benefits, particularly in marketing strategies and policies (Edge et al., 2018; Johnson and Rose, 2013; Kaplan et al., 2018; Teixeira et al., 2021; Van Cauwenberg et al., 2019). Social influence significantly impacts the IA, indicating that societal norms and peer behaviours shape individual decisions (Behrendt, 2018; Kaplan et al., 2015). Positive testimonials and visible usage by peers can enhance the credibility and perceived values. This finding underscores the importance of leveraging social networks and community engagement in promoting shared electric mobility. Although environmental awareness (EA) influences adoption intentions, its effectiveness is smaller compared to other factors, looking to the smaller coefficient. This suggests that while users acknowledge environmental benefits, these alone may not drive the adoption. Practical and social considerations often outweigh environmental concerns, which is consistent with the findings in similar contexts (Bretones and Marquet, 2022). Scepticism negatively influences adoption intentions, reflecting upon the doubts about SEV reliability and underlying car dependency. Users with such perceptions are less likely to adopt SEVs. Addressing scepticism through transparency, consistent service quality, and reliability is critical to mitigate this barrier. Lastly, perceived risk also negatively affects adoption intentions, indicating the concerns about safety, cleanliness, and operational reliability discourage potential users. This finding is consistent with previous research emphasizing risk aversion in shared mobility contexts (Liao et al., 2024; Nematchoua et al., 2020c; Teixeira et al., 2021). Efforts to reduce perceived risks through proper safety measures, such as improved infrastructure accommodating dedicated lanes for safe riding, on-site charging facility for fast and reliable operations can trigger the intentions to adopt SEVs.

5.2. Habitual influence

Habitual use of private vehicles significantly hinders SEV adoption. Mediation analysis further reveals that entrenched travel habits shape perceptions of SEVs by increasing scepticism and perceived risk while reducing perceived usefulness (see Table 3.9). These indirect effects suggest that habitual private vehicle users exhibit higher risk perception and scepticism associated with SEVs, leading to reduced adoption intentions. This highlights the challenge of disrupting established travel patterns, a finding corroborated by number of studies on habit formation and resistance to change (inertia) (Moser et al., 2018; Thorhauge et al., 2020; Valeri and Cherchi, 2016). Breaking these habits requires targeted interventions such as incentives for trial usage or free one-day usage and behavioural nudges.

5.3. Sociodemographic factors

Gender differences reveal that females are less likely to adopt SEVs, possibly due to heightened safety concerns and logistical challenges. This finding aligns with studies that highlight gender-specific barriers in shared mobility adoption. Moderation analysis further highlights this issue as the influence of scepticism (SC) and perceived risk (PR) on IA is stronger amongst females. Age shows a non-significant effect in the current study, which may indicate a broader potential market for SEVs. However, moderating effect of age on relationship between innovativeness and adoption intentions reveals the reduced innovativeness amongst higher age-group which can limit the adoption amongst these individuals. Higher education attainment positively influences adoption intentions, suggesting that educated individuals are more open to innovative and sustainable transportation options, possibly due to more awareness knowledge (Curtale and Liao, 2023a; Mitra and Hess, 2021). Besides, it positively contributes to the perception of an innovative image that shared electric mobility holds among certain user-group. Educational campaigns could further enhance adoption among less-educated groups by emphasizing SEVs' ease of use and benefits. A marginally negative effect of household income on adoption intentions highlights the need to appeal to diverse income segments through flexible pricing models. The presence of children negatively affects the intentions, possibly due to less convenience, family safety and logistical challenges such as child seats which likely deter families from considering SEVs. Service enhancements in this direction such as availing e-cargo bicycles with child configurations (Becker and Rudolf, 2018) and child seats (when required) in e-cars can address this gap. Car ownership strongly discourages adoption intentions, reflecting that the car owners exhibit lower intentions to adopt SEVs. Besides, it also moderates the relationship between PU and IA. In this context, for car owners, the perceived usefulness of SEVs must be demonstrated more compellingly to overcome their preferences for private cars. Health satisfaction's positive influence on adoption intentions indicates that individuals who feel physically well perceive SEVs as viable options. This aligns with findings that link positive health perceptions to greater openness to alternative transportation modes (Avila-Palencia et al., 2018).

5.4. Policy implications

The findings of this study underline the multifaceted factors directly and indirectly influencing the adoption of shared electric mobility, offering actionable insights for planners, policymakers, and operators. Addressing the psychological, habitual, and sociodemographic barriers identified in this research can significantly enhance the SEVs adoption rates and contribute to broader sustainability goals.

Reducing scepticism and perceived risks is pivotal in fostering trust and confidence among potential users. Implementing stringent quality control measures to ensure reliability and service consistency is essential. Safety concerns can be addressed through real-time monitoring systems, in-app emergency features, and secure payment mechanism, which can collectively reduce perceived operational and data privacy risks. These efforts should be complemented by campaigns that emphasize SEVs' practicality, such as cost savings, convenience, and environmental benefits. Highlighting these attributes through targeted marketing strategies can significantly influence perceptions of usefulness and encourage trial usage. Disrupting established habits of private vehicle use requires thoroughly designed incentives and behavioural nudges. Financial incentives may include free day-trials, discounted rates, loyalty programs, and promotional offers which can entice users to try SEVs. Behavioural interventions, such as gamification strategies rewarding frequent users, employer-sponsored commuter subsidies create a favourable context for habit formation (of using SEVs). By encouraging repeated use, these measures help users integrate SEVs into their daily travel routines, gradually replacing reliance on private vehicles. The results reveal that habits indirectly affect adoption intentions by amplifying scepticism and perceived risks while reducing the perceived usefulness. Interventions aimed at breaking these habits, such as restrictions on private vehicles in city centres or the introduction of congestion pricing, can create opportunities for users to explore SEVs. These provisions should be well accompanied by the user-friendly interfaces (i.e, mobile apps) and ample availability of variety of SEVs at shared mobility stations.

The gender gap in SEVs adoption highlights the need for inclusive service designs. Gender-sensitive strategies, including awareness campaigns tailored to women's specific needs can further bolster their confidence in adopting shared electric mobility services. Similarly, family-friendly enhancements are crucial to overcoming barriers for households with children.

Offering features like child seats in shared e-cars, provisions for e-cargo bikes, and subscription packages tailored to family needs makes SEVs practical alternative for family transportation. Further, significant moderating effects of gender and education suggest that interventions should tailored to address specific needs of different demographic groups. For instance, awareness campaigns targeting females should prioritize safety and reliability, while those aimed at highly educated potential users should focus on environmental and technological advantages.

Educational and outreach programs play a significant role in expanding SEV adoption across diverse user groups by shrinking the effects perceived risks and scepticism, while raising the awareness about the benefits (environmental, societal, and economical) of shared electric mobility among younger and employed populations as well as higher income individuals. Younger individuals (<25 years old), who are not yet fully into car ownership/usage culture and usually open to innovative travel options, should essentially be targeted towards sustainable options. This can be achieved by partnering with educational institutions and large workplaces. Simplified communication strategies that emphasize SEVs' usefulness, ease of use and reliability can further encourage adoption among less-educated groups and also help reducing the moderating effect of FTW on association between perceived usefulness and adoption intentions. For higher income groups, offering premium services with enhanced comfort and convenience can also be appealing, positioning SEVs as a viable alternative to private cars. Successful policy implications also hinge on creating an ecosystem that supports shared electric mobility. Connecting potential neighbourhoods with important train, bus, and tram stations through concepts of shared mobility hubs is another vital policy focus. This can enhance the accessibility and convenience, especially for first/last-mile connectivity through micro-modes and consequently boosts adoption rate amongst commuters. It is important to ensure smooth and transparent collaboration between policymakers, private operators, and local communities that is essential to establish safe infrastructure, set regulatory standards, and warrant service reliability.

6. Conclusions

6.1. Remarks

This study provides an in-depth examination of the factors influencing behavioural intentions to adopt shared electric mobility services. By employing latent constructs from the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB) within the Structural Equation Model (SEM) framework, the findings shed light on the psychological, habitual, and sociodemographic determinants of shared electric mobility adoption. These results contribute to a deeper understanding of adoption dynamics, offering insights for formulating interventions that promote SEVs.

Personal innovativeness emerged as a key driver, emphasizing the importance of individual openness to new technologies. Perceived usefulness significantly influenced adoption intentions, highlighting the value of SEVs' practical benefits, including cost savings and convenience. Scepticism and perceived risk were found to be major barriers, deterring potential users, particularly females, by amplifying doubts about reliability, safety, and privacy. Habitual private vehicle usage posed an additional challenge, with direct and indirect effects on reducing adoption intentions by shaping perceptions of SEVs through increased scepticism and risk concerns. The study also revealed significant sociodemographic effects, with gender, education, and household characteristics playing moderating roles. Females reported lower adoption intentions, primarily due to safety concerns, while highly educated individuals demonstrated greater openness to SEVs. The presence of children in households and car ownership negatively influenced adoption, pointing to logistical and competitive barriers that require targeted policy responses.

In conclusion, the policy recommendations derived from this study provide a comprehensive framework for transport planners, policymakers, and service providers paving the way for a sustainable transition to shared electric mobility.

6.2. Study limitations and future work

It is important to note that the sample is limited to a specific geographic and demographic context, potentially affecting the generalizability of results to other regions or populations. Expanding the study to include diverse geographic locations and cross-cultural comparisons could provide more comprehensive insights. The research relies on self-reported data, which may introduce biases such as social desirability or overstatement of intentions and the same should be thoroughly incorporate in policy-making. While this study provides collective insights on adoption of station-based shared electric mobility services, further research could incorporate the similar model framework to specific modes such as e-car, e-bike, e-scooter, and e-cargo bike in a collective manner to gain more insights and compare the attitudes and motivations for adoption of each of these modes. In contrast to previous studies, this study could not find significant effects of age on adoption intentions. This can be due to typically homogenous attitudes of 25-45 years age-group and lack of enough samples from 50+ age-group population. Hence, future study focusing on intentions of older population or collecting data from more diverse age-group can provide more insights here. Though the authors tried to incorporate most general latent constructs looking to their frequency in extant literature and their robustness, there is always room to explore more diverse latent and observable variables such as infrastructure availability, policy incentives, or environmental conditions.

Though the model observed the two-way relationship between habit and scepticism, there is limitation in terms of deriving insights as the data used in this study is cross-sectional which could not confirm the directional causal inferences. In this regard, longitudinal studies are needed to examine how adoption intentions evolve over time, particularly as SEV services mature and user experiences accumulate. Tracking changes in perceptions, habits, and adoption behaviours would provide dynamic insights into the factors driving sustained use. This can also help tracking the impacts of policy interventions framed to address the barriers. Lastly, the derived structural model can be extended to develop advanced integrated choice models to examine the impacts of these latent constructs on individuals' travel choice preferences. Authors intend to reflect upon these issues in their future work.

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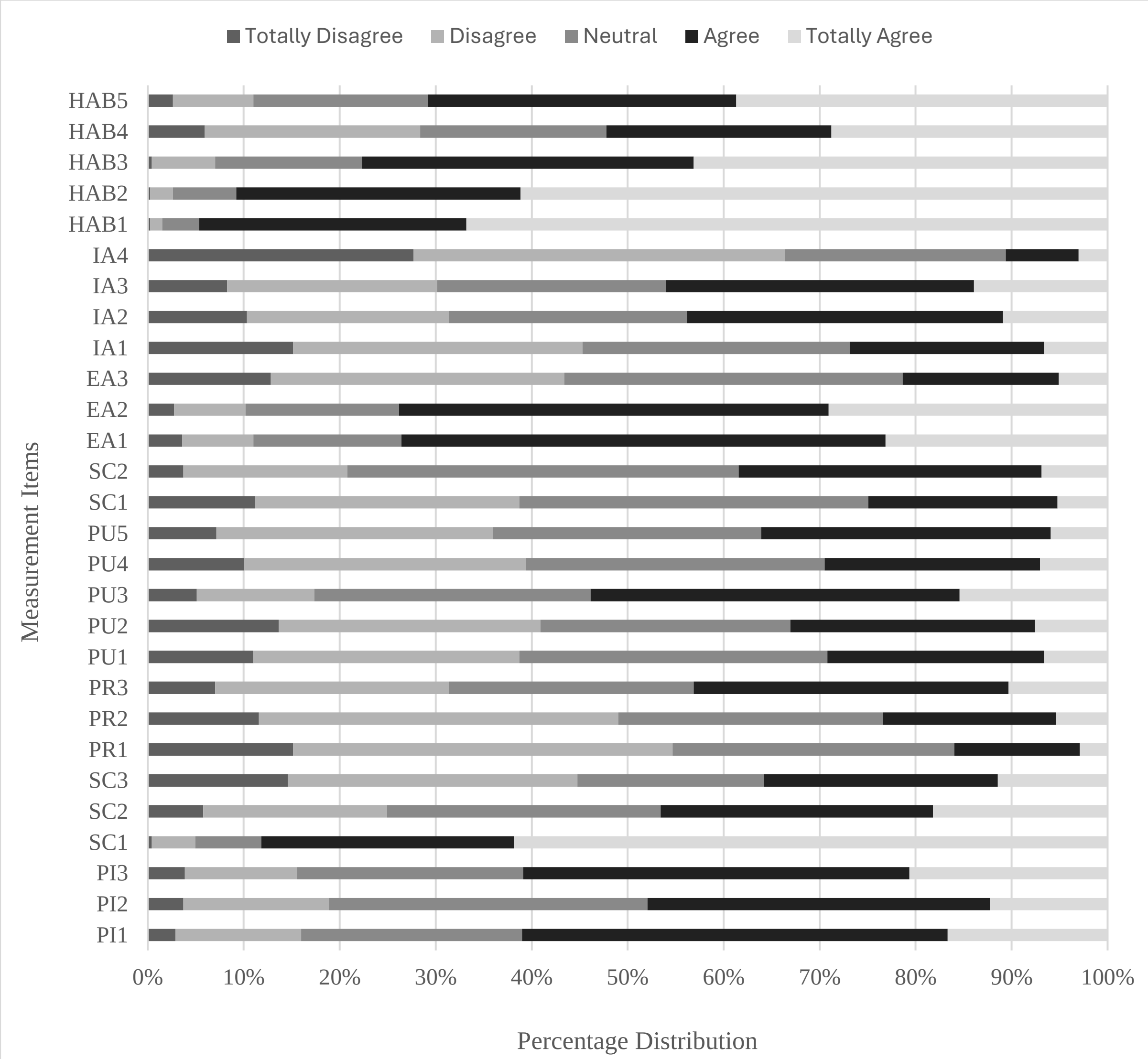
Appendix to Chapter 3

Appendix 3.1. Descriptive Statistics of the measurement items.

Item	N	Mean	Std. Deviation	Skewness	Kurtosis
EA1	726	3.82	0.987	-0.998	0.817
EA2	726	3.9	0.994	-0.931	0.559
EA3	726	2.7	1.048	0.213	-0.469
PI1	726	3.59	1.006	-0.564	-0.221
PI2	726	3.38	1.004	-0.298	-0.384
PI3	726	3.62	1.056	-0.585	-0.238
PU1	726	2.86	1.091	0.074	-0.705
PU2	726	2.86	1.166	0.042	-0.933
PU3	726	3.47	1.054	-0.491	-0.263
PU4	726	2.87	1.089	0.117	-0.709
PU5	726	2.99	1.056	-0.041	-0.833
PR1	726	2.49	0.995	0.406	-0.314
PR2	726	2.68	1.064	0.352	-0.57
PR3	726	3.15	1.116	-0.155	-0.857
SC1	726	4.45	0.842	-1.62	2.184
SC2	726	3.34	1.149	-0.199	-0.816
SC3	726	2.88	1.255	0.133	-1.098
SI1	726	2.8	1.044	0.087	-0.536
SI2	726	3.21	0.932	-0.189	-0.224
SI3	726	2.77	1.121	0.111	-0.885
hab1	726	4.6	0.653	-1.869	4.379
hab2	726	4.49	0.746	-1.576	2.512
hab3	726	4.13	0.932	-0.883	0.015
hab4	726	3.47	1.277	-0.263	-1.172
hab5	726	3.96	1.068	-0.851	-0.023
int1	726	2.73	1.142	0.197	-0.798
int2	726	3.13	1.172	-0.232	-0.878
int3	726	3.21	1.176	-0.214	-0.899
int4	726	2.2	1.023	0.711	0.071

Appendix 3.2. Distribution of respondents' ratings to measurement items.



Chapter 4

Modeling shared electric mobility adoption: insights from a hybrid latent-class and latent-variable approach

Abstract

Shared electric mobility system holds significant potential to direct urban transport towards sustainability. By offering flexible and sustainable alternatives such as e-cars, e-bikes, and e-scooters, it can reduce private car dependency, thus alleviating traffic congestion, and improving air quality. However, the adoption rates of shared electric mobility remain subdued and less is known about the dynamics of shared electric mobility and traditional transport options. This study investigates the adoption of shared electric mobility through stated preference data from a web-based survey conducted in different cities of England. A hybrid Latent-Class Latent-Variable model is proposed for this purpose in which latent class segmentation is conditional upon the sociodemographic characteristics and mode-use habit, whereas mode-specific attributes and several latent constructs were incorporated in the class-specific choice models. Results reveal two distinct latent classes with distinct preferences towards shared electric mobility alternatives. It is identified that non-habitual individuals, characteristically public transport friendly and price sensitive, are more likely to use shared electric mobility. While these individuals are more inclined to micro-mobility options, car users tend to prefer shared e-cars over other shared electric mobility modes. Substitution patterns reveal positive shift from private cars to shared electric mobility modes, and also unintended shift from public transport to shared electric mobility modes. Based on the empirical results, several key policy interventions are discussed that provide valuable insights into the dynamics of shared electric mobility adoption and its potential impacts on urban transport systems.

Keywords: Attitudes; Commuting travel behaviour; Hybrid choice model; Latent class model; Micromobility; Mode substitution; Shared electric mobility

1. Introduction

The transportation sector worldwide is experiencing a critical transformation fuelled by technological innovations, environmental concerns, and changing consumer preferences. As urban populations continue to rise, cities face increasing challenges related to traffic congestion, air pollution, and greenhouse gas (GHG) emissions. Due to traditionally heavy reliance on private cars, cities are becoming more and more unsustainable looking to its environmental, social, and economic impacts. The transportation sector is one of the largest contributors to carbon emissions, accounting for ~24% of global CO_2 emissions, largely from internal combustion engines (ICE) vehicles (World Resources Institute, 2019). The dominance of private vehicles in urban areas exacerbates air quality issues linked to climate change and leads to significant economic losses due to traffic congestion. For instance, in the United Kingdom, cities like London grapple with severe congestion, costing £4.9 billion in 2019[10] and is expected to incur £9.3 billion in 2030[11]. Other cities following the same route– an average Birmingham driver lost 37 hours per year in congestion costing a total £346 million in 2022, which was more than 1% of the city's total economic output[12]. Governments and policymakers across the globe are increasingly taking efforts to address these externalities and focus towards sustainable and equitable transportation. These include the promotion of active and shared transport modes, emphasise on public transport infrastructure, and the formulation of low-emission zones to curb vehicular pollution. Countries such as the Netherlands, Germany, France, and UK have formulated several policy measures in light of promoting cycling and shared mobility systems, recognizing their potential to transform urban transport landscapes.

Shared electric mobility system (SEMS) holds significant potential to direct urban transport towards sustainability (Bösehans et al., 2024b; Fukushige et al., 2021b; Jie et al., 2021). By offering flexible and sustainable alternatives such as e-cars, e-bikes, and e-scooters, it can reduce dependence on private vehicles, thus alleviating traffic congestion, and improving air quality. Moreover, integrating shared electric mobility with public transport system can improve first- and last-mile connectivity, enhancing overall accessibility and convenience (Montes et al., 2023; Oeschger et al., 2020). SEMS reduces the carbon footprints associated with urban trips, contributing to global efforts to prevent environmental degradation. Besides, it fosters inclusivity by providing affordable and equitable transportation options, particularly for individuals who may not have access to private vehicles and are not well served by public transport facilities (Guan et al., 2024; Mohiuddin et al., 2023). Economically, SEMS can optimize the resource utilization, free up public space used for private vehicle parking, and reduce infrastructure costs. Despite the growing interest in SEMS and its potential to combat current transport challenges, the adoption rates remain subdued and its current state within existing transportation system is unclear (Aba and Esztergár-Kiss, 2023). Much of the existing literature knowledge revolve around individual shared modes, such as e-bike sharing or e-

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[10] Refer to Transport for London's press release.
[11] Refer to press release from INRIX.
[12] Refer to published article from The Dispatch.

scooter sharing, while the comparative dynamics among the shared options is relatively less known, except a few recent attempts (e.g., (Abouelela et al., 2021; Bösehans et al., 2023a; Brezovec and Hampl, 2021; Curtale and Liao, 2023b; Krauss et al., 2022; Liao et al., 2024). Further, the interaction between these shared modes and traditional public transport modes remains underexplored and receiving more interest from researchers in recent years. While some of these studies reveal complementarity of shared micromobility with public transport, others unveil the contradictory results with shared mobility as competitive alternative to public transport. Therefore, it is imperative that this relationship is thoroughly investigated which may otherwise limit the development of comprehensive solutions.

From the few recent studies focusing on dynamics of shared electric modes, the primary focus remains on the mode-specific attributes (e.g., travel cost and time), socio-demographic characteristics, and built-environment factors with some studies expanding health, weather and season-specific variables (Abouelela et al., 2021; Curtale and Liao, 2023b; Hosseinzadeh et al., 2021). Nonetheless, the travel behaviour of these emerging transport alternatives may not be the only function of these parameters, but also of the individuals' psychometric attributes such as values, attitudes, and perceptions (Chen et al., 2021; Eccarius and Lu, 2020b; Kim and Rasouli, 2022; Parmar et al., 2023b) towards current as well as shared modes. This gap remains unaddressed in the extant literature. What's more, routine travel behaviour, for example, the daily commute mode choice, may become habitual and automated (Aarts and Dijksterhuis, 2000; Verplanken et al., 1998). People often choose most appealing alternative when presented with unfamiliar choice situation in order to make logical, goal-oriented decisions (Aarts et al., 1998). When a goal-behaviour link is established, it remains in stable condition if the associated goal-achievement link is positively reinforced (Gardner, 2009; Gärling et al., 2001). Over the time, repeated actions strengthen this association, making the behaviour automatic and habitual. In essence, individual's decision-making behaviour (i.e., choice to travel mode) differs across different group with varied habitual patterns. Thus, examining how habits influence these choices across different segments of users is essential to assess the heterogeneity in decision-making process.

With this background, this research seeks to fill the gaps in current literature by investigating the adoption of station-based shared electric mobility systems, including shared e-cars, e-bikes, and e-scooters, as viable alternatives to private vehicle usage. To achieve this, this study introduces a hybrid latent class latent variable (LCLV) model which integrates two distinct approaches: Integrated Choice and Latent Variable (ICLV) model and Latent Class Choice Model (LCCM). The simplified objectives of this study include:

1. Investigating dynamics of travel choice behaviour across shared e-cars, shared e-bikes, shared e-scooters, private cars, and public transport.
2. Operationalising segmentation of commuters into discrete latent classes based on mode-use habit and sociodemographic variables.
3. Incorporating individual-level psychometric attributes and stated-choice data into distinct latent class choice models.

4. Drawing important conclusions and providing valuable recommendations that encourage the adoption of station-based shared electric mobility.

The next section gives contextual overview of existing literature on adoption of SEMS. The chapter then moves on to the discussion of research methods, survey and materials in Section 3. Section 4 presents the analysis results, while Section 5 describes the outcomes of the study and discusses the policy implications. At last, Section 6 concludes this study with summary, limitations of the present study, and potential future work.

2. Review of the relevant literature

2.1. Travel behaviour and shared electric mobility

By delving in to the existing studies, this subsection explores how the adoption of shared electric mobility is influenced by range of variables, typically classified as sociodemographic characteristics, psychological attitudes, mode-specific level-of-service attributes, as well as external factors such as weather. Sociodemographic parameters such as age, gender, income, and education level influence users' behaviour and adoption (Amirnazmiafshar and Diana, 2022; Bretones and Marquet, 2022). In general, younger and educated people, particularly those in urban settings, are more likely to use SEMS because of their familiarity with technology and openness to innovation (Bretones and Marquet, 2022; Curtale and Liao, 2023b). Male individuals are generally more inclined towards SEMS, possibly due to higher reluctance and risk-aversion amongst females (Bösehans et al., 2023b; Kawgan-Kagan, 2015). Travel-oriented characteristics, such as, cost and time-savings (Krauss et al., 2022; Liao et al., 2024), convenience (McBain et al., 2023; Schaefers, 2013), usefulness and ease of use (Bretones and Marquet, 2022; Samadzad et al., 2023), accessibility and flexibility (Baek et al., 2021; Guan et al., 2024; Lee et al., 2021), and reliability (Jin et al., 2020; Xia et al., 2022) are often cited as the most common determinants for SEMS adoption and intentions-to-use. For example, users perceive that SEMS can save them money, when compared to owning and maintaining a private car (Chicco et al., 2022; Kim et al., 2015), while the present cost (usage fees) has negative association with the use of SEMS (Bobičić and Esztergár-Kiss, 2024; Bretones and Marquet, 2022). Studies also reveal that using SEMS perceived positively amongst adopters stating, "convenient for everyday use or commuting, improving travel independence" (Bösehans et al., 2024b), "can ease access to mobility and other transport options (such as public transit)" (Baek et al., 2021; Mohiuddin et al., 2023), and "reduced total commute time, particularly with micro-modes as they pass conveniently through traffic in peak times" (Zhao et al., 2022). Weather and seasonal factors considerably affect SEMS usage patterns, particularly for micro-modes. Rain and extreme temperatures are key deterrents, for example, (Hosseinzadeh et al., 2021) found ~17% decline in shared e-bike usage during rainy weather. Winter months witness steep decline in SEMS use, though the sensitivity varies by mode and user demographics (Mathew et al., 2019).

Apart from these, socio-psychological factors deemed to have significant impact on users' preferences for SEMS, generally based on ICLV models. Personal attitudes such as environmental awareness, perceived safety, and personal innovativeness are often found significantly influencing SEMS use (Bieliński et al., 2020; Edel et al., 2021; Kaplan et al., 2015). A review by (Bretones and Marquet, 2022) emphasized that non-functional values such as social norms and emotional satisfaction can outweigh functional considerations like cost or time savings. For instance, individuals who perceive SEMS as socially beneficial and aligned with modern urban living are more likely to adopt them. Studies dealing with technology acceptance model (TAM) found that factors such as perceived usefulness and personal innovativeness have positive impacts particularly amongst early adopters (Wang et al., 2020). Perceived risk and reliability are also repeatedly found to negatively influencing the early adoption of micro-modes, particularly in association with unsafe and inefficient infrastructure at current juncture (Flores and Jansson, 2021b; Krauss et al., 2022).

Over the time, there is abundant literature examines the role of mode-use habit (or inertia) in shaping travel behaviour and mode choice (Cherchi and Manca, 2011; Thorhauge et al., 2020; Valeri and Cherchi, 2016). It is believed that individuals with established travel routines, such as commuting mode choice, are less likely to consider unfamiliar alternatives (Gardner, 2015), unless driven by strong motives when underlying habit is weak (de Kruijf et al., 2018; Gössling, 2020b). Conversely, individuals with existing multimodal habits are more prone to integrate SEMS in their travel patterns (Gössling, 2020b; Moser et al., 2018). Habit has been commonly operationalised through either self-reported frequency measure i.e., how many times a specific mode is used (Triandis, 1977) or through latent construct, where it is recognized as individual's attitude formed over time (Cherchi et al., 2014). However, retrospective single-item measure of self-reported frequency may not be optimal in terms of reliability and validity while evaluating the role of habit in behaviour (Gardner, 2012; Wright et al., 1997). While most studies conceptualize direct or interaction effects of habit in discrete choice models (Cherchi and Cirillo, 2014; Klöckner and Matthies, 2004; Verplanken et al., 2008), the other approach can be to classify group of individuals into segments based upon the intensity of habit. Based upon the discussions by (Shen, 2009; Wedel and Kamakura, 1999), the later approach may be more beneficial while formulating targeted implications where the aim is to break habitual travel behaviour (such as car-use). Therefore, this study employs habit as a latent construct to classify commuters based on their habit strength using LCC model.

2.2. Shared electric mobility – substitution and complementarity

Only small number of studies investigate the complement and substitution relationships that can be SEMS + other traditional modes and SEMS vs. other traditional modes. In essence, complementarity arises when the shared electric mobility enhances the demand/attractiveness for other modes (such as public transport), and vice versa is the case of substitution. This subsection briefly discusses these relationships based on the current literature. Several studies have found that SEMS modes enhance the efficiency and attractiveness of traditional public transport by addressing first-mile and last-mile connectivity issues (Li et al., 2024; Montes et al., 2023; Oeschger et al., 2020; Rossetti et al., 2023; van Kuijk et al., 2022; Zuniga-Garcia et al., 2022b). E-scooters and e-bikes are particularly effective in bridging gap between public transport stations and final destinations, extending the catchment area of public transport systems (Shaheen and Chan, 2016). Given the benefits of public transport and SEMS, this integration can positively contribute towards environmental and economic improvements, and ultimately to social welfare (Oeschger et al., 2020; Chapter 2). Bobičić & Esztergár-Kiss (2024) and Dill et al. (2022) posed that introduction of such services in low-density areas of a city, particularly underserved by public transport, can improve the transit coverage and adoption.

Some argue that SEMS modes also compete with other traditional modes (Bösehans et al., 2024a; Curtale and Liao, 2023b; Kim et al., 2015; Le Vine and Polak, 2019; Liao et al., 2024). This can be favourable if they substitute private cars and unfavourable in case of public transport modes. The impacts SEMS in reducing car-use is well discussed in the literature. For example, it was found that every station-based shared car replaced 11 private cars in the Netherlands (Oldenburger et al., 2019), whereas in Bremen, Germany, every shared car replaced 15 private cars (Schreier et al., 2018). However, based on longitudinal study, (Becker et al., 2018) found much lower reduction of ~6% in car ownership for free-floating carsharing services. (Kolleck, 2021) studied substitution pattern in 35 German cities and revealed that one station-based car replaced ~9 private cars. However, the results were not positive in case of free-floating services, as it did not lead to reduced car ownership. Studies also reveal that in high density areas, congested parts of city such as central areas, and areas with overcrowding in public transport modes, SEMS modes tend to substitute public transport, especially for shorter trips, as they can offer direct and faster options (APTA, 2016; McKenzie, 2020; Oehme et al., 2022). Further, bike sharing and e-scooter sharing were also found to replace walking, which was otherwise the most common mode of transport for short trips (Laa and Leth, 2020; Reck et al., 2022). Such relationships may well depend upon the individual characteristics, attitudes, vehicle ownership levels, state of public transport, and feature of SEMS modes.

3. Survey and data description

3.1. Survey design

A web-based questionnaire survey was formulated accommodating several sections to collect individual-level data relevant to the study objectives. At the starting of the survey, participants were given a brief explanation of the station-based shared electric mobility services through text and picture. The survey consisted of four parts:

- Travelers' current mobility pattern including accessibility parameters and their sentiments regarding current mode of travel
- Stated choice experiments for commute mode choice
- Traveler's psychometric characteristics regarding their current mode and SEMS
- Sociodemographic parameters

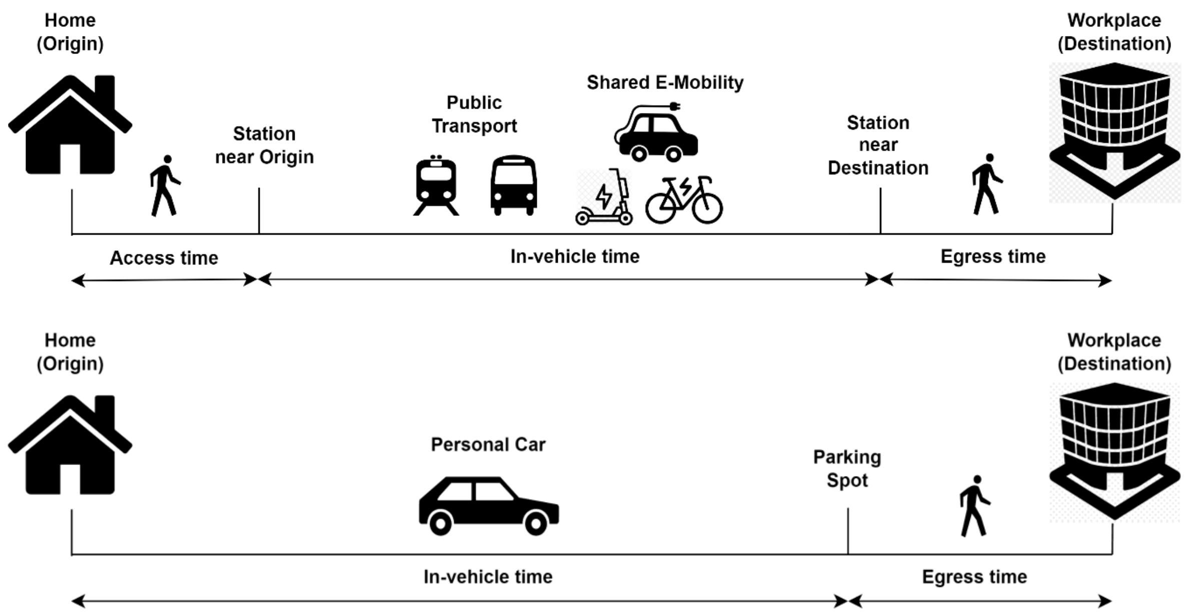

Figure 4.1 Schematics of choice tasks for short trips.

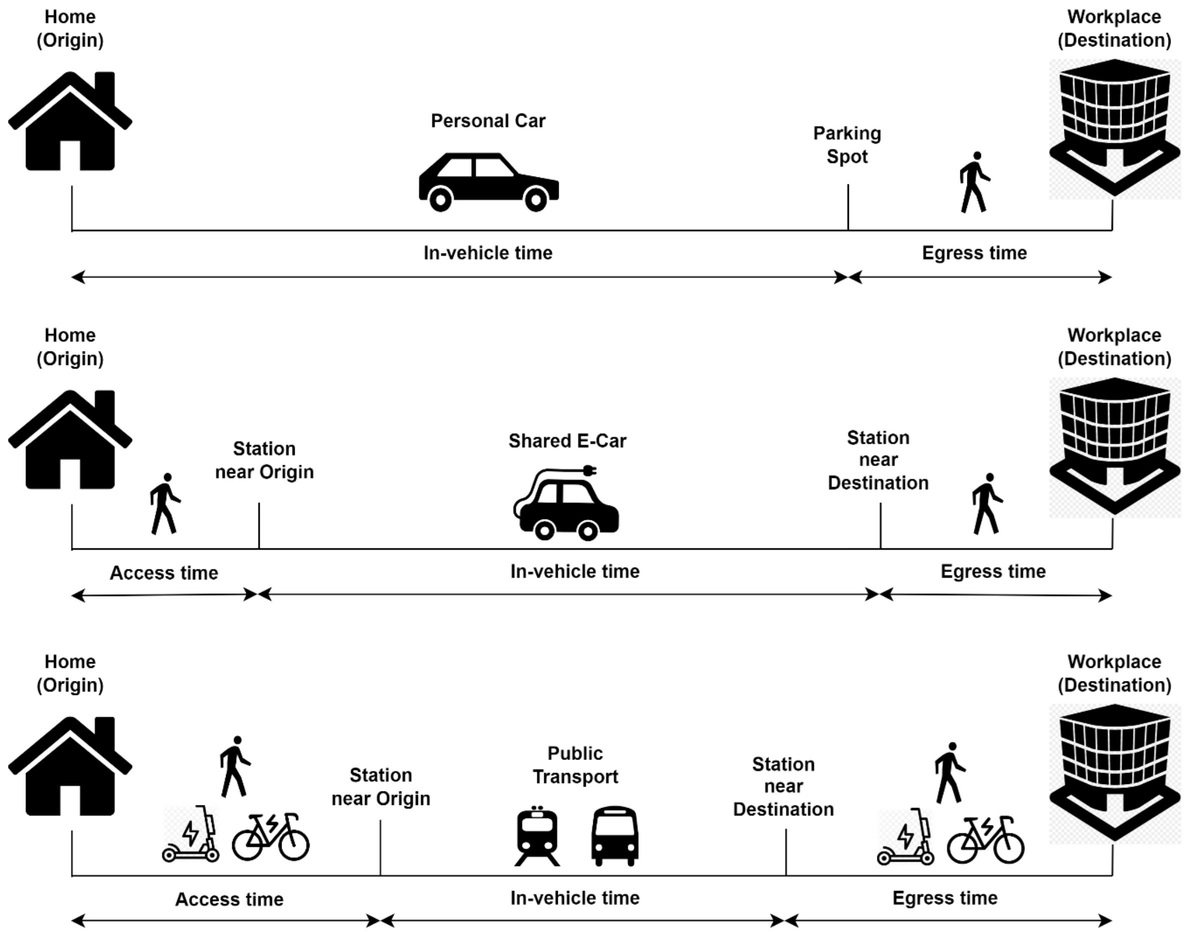

Figure 4.2 Schematics of choice tasks for long trips.

Since this study is focused on commuting trips and station-based SEMS in urban context, several criteria were considered for screening eligible participants: 1) commute at least two days in a typical 5-day working week (to obtain responses from those possessing enough experience); 2) frequently commute using private car and/or public transport (to focus on substitution of these modes); 3) one-way trip no longer than 15 km (to ensure the trips are intra-city and feasibility of SEMS stations); 4) possess driving license (to ensure that they can drive shared e-car). It is assumed that the SEMS is one-way, i.e., users can pick-up and drop-off the shared vehicles at different stations within the city and parking space is always available at SEMS stations neglecting extra time to search for parking space.

For stated choice experiment design, this study adopted D-efficient design with labelled alternatives generated using the experimental design software Ngene[13]. The design was generated for two base-case scenarios: 1) short commute (<= 5 km), and 2) long commute (>= 5 km). A 5 km threshold was fixed as the majority of the trips taken using shared e-bikes and e-scooters fall within this distance (Liao and Correia, 2022). Survey participants were presented with one of these scenarios based on their current commute trip distance. Since the mode choice is expected to be different for these categories, different set of alternatives were considered for each scenario. For short commute, participants could choose from five alternatives: private car, public transport, shared e-car, shared e-bike, and shared e-scooter. For long commute, participants could choose from three alternatives: private car, public transport, and shared e-car. Further, when respondents choose public transport for long trips, they were presented with additional choice tasks for access/egress to transit with three alternatives: shared e-bike, shared e-scooter, and walking. Thus, a two-step approach was adopted for long commute trips which includes two mode choice decisions related to each other. Before starting of this section in online survey, participants were given enough knowledge about the choice tasks through text and relevant figures (refer to Figure 4.1 and 4.2).

Two types of variables were measured through SC experiments: contextual variables and alternative-specific variables. The contextual variables represent the assumptions under which the participants could make their choices. In this study, two variables characterising the weather (rainy or sunny) and temperature (≤ 10°C or > 10°C) were included to explore the effects of these variables on choice decisions. The alternative-specific variables characterise the nature of trip performed using that alternative. Relevance to the objectives and scope of the study, variables associated with time (in-vehicle time, access/egress time), cost (travel cost, parking cost), and convenience (%Availability, waiting time) were included in the choice tasks. Tables 4.1, 4.2 and 4.3 present the list of attributes for three type of choice scenarios with their levels. To ensure realistic attribute levels of time, different combinations of origin-destination pairs within the city limits were tested using Google maps. For costs, web exploration was carried out to verify across various sources of existing shared e-mobility services. A variable *Availability (%)* denotes the probability (or percentage of times) of immediate availability of SEMS modes when required. Further, *waiting time* of SEMS modes denote the delayed time

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[13] https://www.choice-metrics.com

when they are not immediately available. Please note that these variables were varied across three SEMS modes to investigate the substitution when *availability (%)* of a SEMS mode is less.

For the survey, a D-efficient design with 45 choice tasks in five blocks for short trips, 36 choice tasks with six blocks for long trips, and additional 30 choice tasks with five blocks for access/egress trips were generated. Therefore, participants were faced nine choice tasks in case of short trips. While in case of long trips, participants were confronted six tasks for main-haul trip with additional six tasks for access/egress trips provided they would choose to travel with public transport. Figure 4.3 shows an example of a choice task presented for short trips.

In third part of the survey, participants were asked to declare their level of agreement on several statements intended to measure their psychometric attitudes towards current mode of transport as well as SEMS. A total 20 statements were formulated to extract latent variables (LVs) such as personal innovativeness, environmental awareness, social influence, scepticism, perceived risk, and perceived usefulness (see Chapter 3). Additional five statements were formulated to evaluate and extract latent construct for mode-use habit. The statements used for habit were based on the 12-item Self-Report index of habit strength (Beirão and Cabral, 2008; Verplanken and Orbell, 2003). All these 25 statements were evaluated on a 5-point Likert's scale ranging from 1 = "totally disagree" to 5 = "totally agree" with middle point 3 = "neutral".

Table 4.1 Attributes and levels for short trips.

Attribute	**Car**	**PT**	**Shared e-car**	**Shared e-bike**	**Shared e-scooter**
Weather			Sunny, Rainy		
Temperature			≤ 10°C, > 10°C		
In-vehicle time (min)	8, 12, 16	9, 14, 18	8, 12, 16	7, 11, 15	8, 12, 16
Access time (min)	-	2, 6, 10		4, 7, 10	
Egress time (min)	5, 8, 11	2, 6, 10	4, 7, 10		
Waiting time (min)	-	4, 7, 10	5, 7	3, 5	3, 5
Travel cost (£)	0.5, 0.8, 1.2	1, 1.4, 1.8	3, 5, 7	2, 3.5, 5	
Parking Cost (£)	0, 5, 10	-	-	-	-
Availability (%)	-	-		50, 75, 100	

Table 4.2 Attribute and levels for long trips.

Attribute	**Car**	**PT**	**Shared e-car**
Weather		Sunny, Rainy	
Temperature		≤ 10°C, > 10°C	

In-vehicle time (min)	20, 25, 30	25, 30, 35	20, 25, 30
Access time (min)	-	*Pertaining to access/egress mode choice*	5, 8, 11
Egress time (min)	5, 8, 11		5, 8, 11
Waiting time (min)	-	4, 7, 10	5, 7
Travel cost (£)	1.5, 2, 2.5	1.5, 2, 2.5	5, 7.5, 10
Parking Cost (£)	0, 5, 10	-	-
Availability (%)	-	-	50, 75, 100

Table 4.3 Attributes and levels for access/egress trips to public transport.

Attribute	Shared e-bike	Shared e-scooter	Walking
Weather	Sunny, Rainy		
Temperature	≤ 10°C, > 10°C		
In-vehicle time (min)	3, 5, 7	3, 5, 7	-
Walking time (min)	4, 7, 10		10, 15, 20
Travel cost (£)	0.5, 1, 1.5		-
Waiting time (min)	3, 5		-
Availability (%)	50, 75, 100		-

3.2. Data collection and description

The survey was administered in the England during July/August 2024. A pilot test was conducted internally earlier in March 2024 to gain insights from experts in SC experimental design, followed by a soft launch in April 2024 with 52 responses. Following the validation of attributes in stated choice experiments, a full-phase survey was carried out. Several cities including, Birmingham, Manchester, Liverpool, Leeds, Nottingham, and Sheffield were selected for this study. These cities exhibit comparable demographics, transport infrastructure including availability of shared electric mobility services, economic profile, and car-dominant commute which makes it suitable to operationalise aggregated behavioural data. Participants were recruited using an online panel for market research which allowed for control in terms of sample representativeness. After excluding ineligible participants and removing unengaged/poorly-attended samples, 726 observations were considered for the further analysis. Table 4.4 summarises the overview of sociodemographic variables for the final sub-sample.

The sample is slightly overrepresented by the females (55.8%) and underrepresented by the males (44.2%) compared to the UK national average (female proportion of ~51%). The largest age group falls between 25-34 years (34.16%), followed by 35-44 years (27.1%), with only 1.38% of respondents being older than 65 years. Education levels show a high representation of undergraduates (46.3%) and postgraduates (24.7%), which reveals high biasedness towards higher qualified respondents. Employment status indicates that most participants are full-time workers (67.2%), while part-time workers account for 24.1%. With higher percentage of full-time working and highly qualified respondents, more than 60% of them having household income greater than £40,000, while only slight proportion of the respondents (5.9%) earn lesser than £20,000. Household demographics show that 52.9% have two adults, 21.5% have three adults, and 47.2% have children, which are somewhat near to the UK census. Car ownership is common, with 95% of households owning at least one car, while bicycle ownership is slightly less prevalent, with 38.84% owning none.

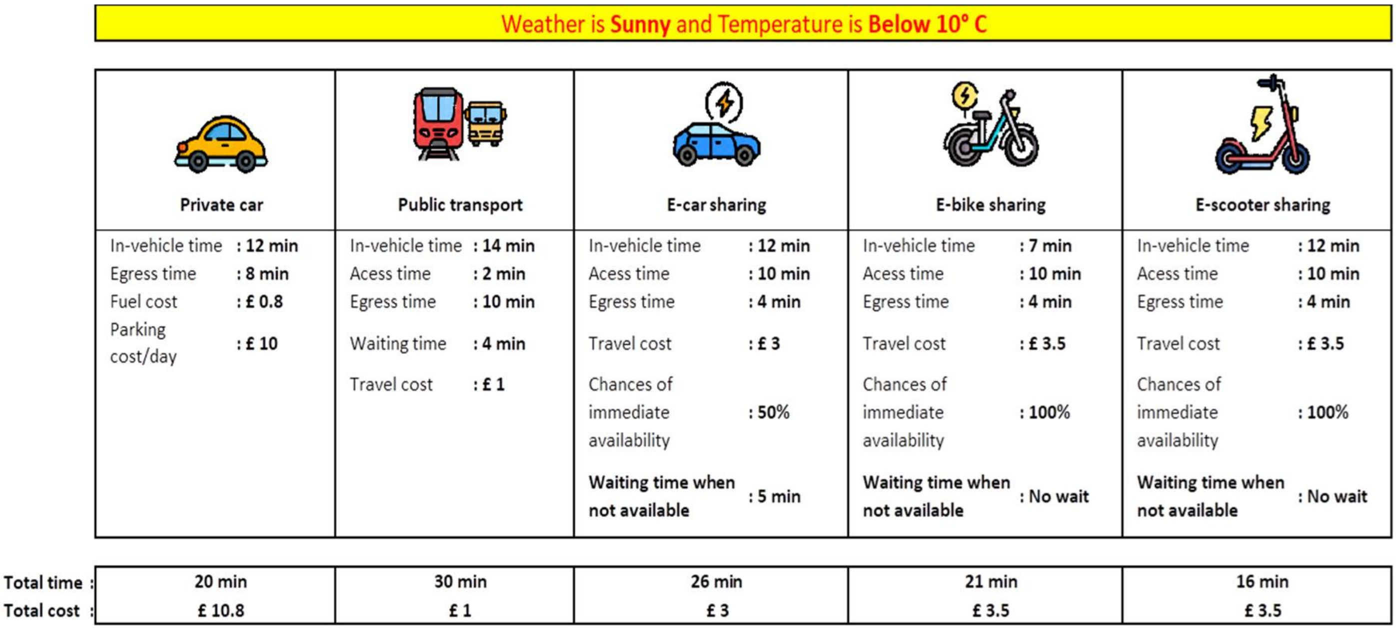

Figure 4.3 Example of choice tasks (short trip).

Table 4.4 Descriptive statistics of the survey participants (N=726).

Characteristics	Levels	Frequency	Proportion (%)
Gender	Female	405	55.79%
	Male	321	44.21%
Age	18-24	70	9.64%
	25-34	248	34.16%
	35-44	197	27.13%
	45-54	133	18.32%
	55-64	68	9.37%
	65 and older	10	1.38%
Education level	Primary School	0	0.00%
	Secondary School	183	25.21%
	Undergraduation	336	46.28%
	Postgraduation	179	24.66%

	Professional qualification	28	3.86%
Employment	Full-time worker	488	67.22%
	Part-time worker	175	24.10%
	Self-employed	42	5.79%
	Business	2	0.28%
	Student	19	2.62%
Income level (yearly)	< £20,000	43	5.92%
	£20,000 - £39,999	230	31.68%
	£40,000 - £59,999	156	21.49%
	£60,000 - £79,999	150	20.66%
	£80,000 - £99,999	108	14.88%
	> £100,000	39	5.37%
Adults in household	One	94	12.95%
	Two	384	52.89%
	Three	156	21.49%
	Four or more	92	12.67%
Children in household	Yes	343	47.25%
	No	383	52.75%
Number of cars in household	Zero	33	4.55%
	One	363	50.00%
	Two	288	39.67%
	Three or more	42	5.79%
Number of bicycles in household	Zero	282	38.84%
	One	219	30.17%
	Two	124	17.08%
	Three or more	101	13.91%
Satisfaction with health	On 10-point scale	**Mean (SD)**	7.31 (1.79)

In terms of current most frequent commute mode, 75% of the respondents selected private cars and 18% selected public transport. Further, 10% of the respondents stated private cars as second most frequent commute mode, while 32.5% selected public transport. In essence, 85% of the respondents frequently use private cars and 50.5% of them frequently use public transport for their commute. This covers the entire sub-sample. The remaining respondents (in case of most frequent mode) use private or shared bike, moped or car (as a passenger) for their commute, which is collectively 7%.

4. Model formulation

The model was formulated within the framework of random utility maximization theory, which postulates that an individual's choice, amongst mutually exclusive and collectively exhaustive alternatives, is based upon the alternative yielding the highest utility. As mentioned before, this study adopted an integrated latent class latent variable (LCLV) which integrates two distinct approaches: Integrated Choice and Latent Variable (ICLV) model and Latent Class Choice Model (LCCM). Both these models have been widely applied to econometric studies in transportation context, such as, mode choice (Hurtubia et al., 2014; Molin et al., 2016; Parmar et al., 2023b), route choice (Arriagada et al., 2022; Motoaki and Daziano, 2015), and electric vehicle purchase decisions (Oryani et al., 2022; Soto et al., 2018). The ICLV model consists of two parts: a discrete choice model evaluating the utilities of studied alternatives, and a latent variable model, which extracts the unobservable latent constructs from the underlying observed measurement indicators (Ben-Akiva et al., 2002). The latent variables in this case are continuous random variables. In this study, ICLV model structure was used to evaluate the alternative-specific utility as a function of alternative-specific attributes and latent variables. The LCCM is a probabilistic clustering method aimed at dismantling a multivariate discrete population into distinct subgroup such that the population within the latent cluster remains homogeneous and exhibits heterogeneity to other clusters. Unlike ICLV model, LCCM sees latent variables as discrete constructs. In this study, LCCM was deployed to segment population into distinct latent clusters based upon the sociodemographic characteristics and mode-use habit. The schematic diagram of the proposed model is presented in Figure 4.4. Observed variables are shown in rectangular boxes, while unobserved variables are shown in ellipses. The measurement relationships are depicted with dashed lines and structural relationships are presented with continuous lines.

4.1. Structural model for latent constructs

The structural equations describing latent variables in terms of observed exogeneous variables (i.e., sociodemographic parameters in this study) can be written as:

$$\alpha_i = \Gamma z_i + \eta_i, \qquad \eta_i \sim N(0,1) \tag{4.1}$$

where α_i is endogenous latent construct for an individual $i \in (1,...,N)$; z_i is the vector of sociodemographic characteristics of an individual i explaining the latent variables; Γ is a vector corresponding to the parameters to be estimated; and η_i is a structural error term assumed to be normally distributed with zero mean and unite variance. The latent variables here are identified through multiple measurement indicators as per the following equation:

$$I_i = \zeta_i \alpha_i + \varepsilon_i, \qquad \varepsilon_i \sim MVN(0, \Sigma_\varepsilon) \tag{4.2}$$

$$I_{id} = \begin{cases} 1, & if\ \tau_{0d} < I_{id} \le \tau_{1d} \\ 2, & if\ \tau_{1d} < I_{id} \le \tau_{2d} \\ \vdots & \\ k, & if\ \tau_{(k-1)d} < I_{id} \le \tau_{kd} \end{cases}, \quad \forall d \in D \tag{4.3}$$

where I_i belongs to the vector of measurement indicators of a latent construct; ζ_i is a vector of unknown parameters to be estimated; and ε_i is measurement error following multivariate normal distribution with zero mean and $(D \times D)$ identity covariance matrix, where D is the number of indicators for a given latent construct. Equation 4.3 represents the observed response for d-th measurement indicator; when an individual chooses k in ordinal Likert's scale for a given measurement indicator, the corresponding latent construct lies in a range between $\tau_{(k-1)d}$ and τ_{kd}. For model identification, k – 1 threshold parameters need to be estimated. For all indicators, k remains five as they are evaluated on 5-point scale.

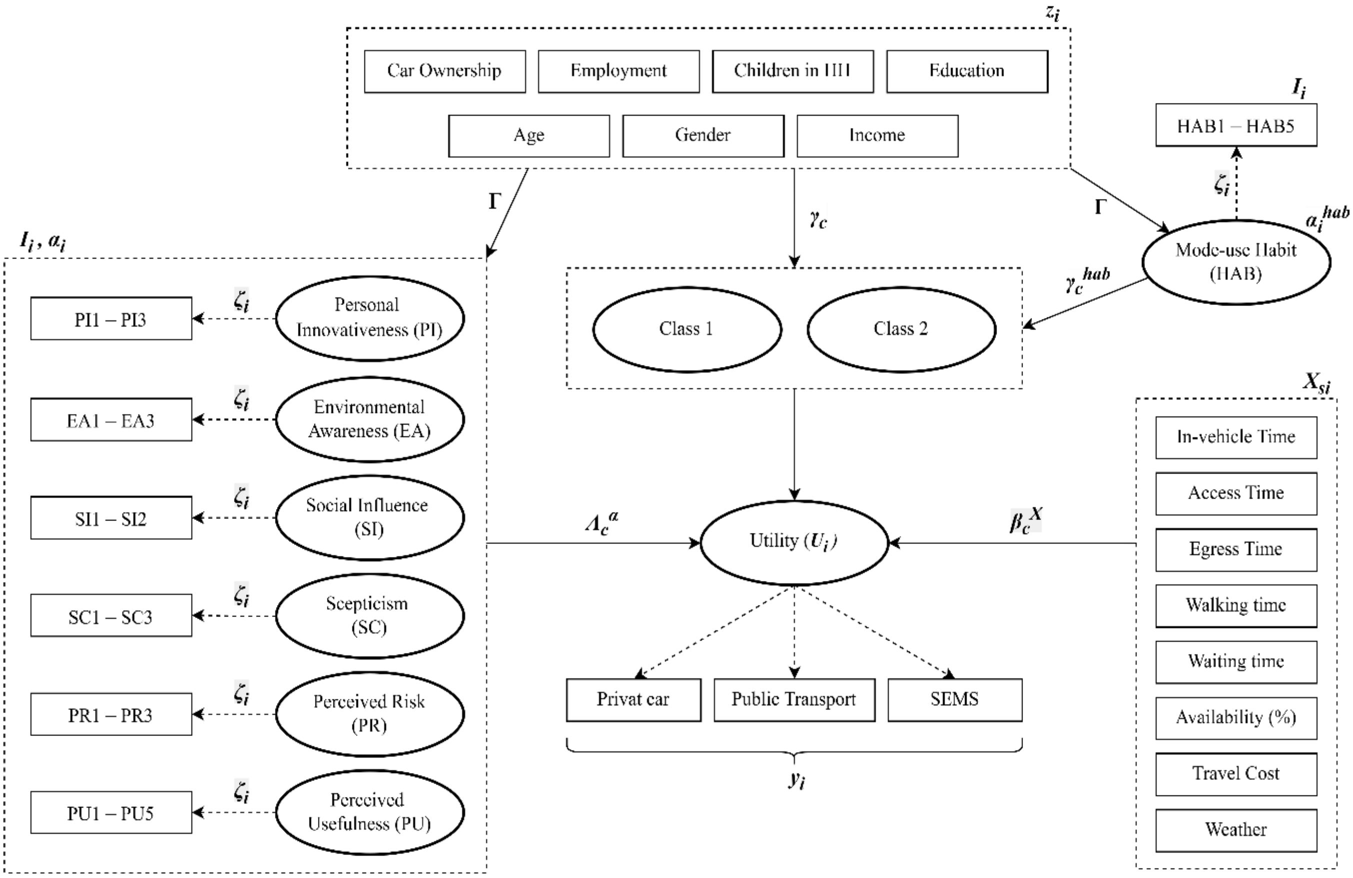

Figure 4.4 Proposed model framework.

The measurement equations were estimated using an ordinal logit model where the measurement indicators are treated as ordinal variables. The likelihood of the observed responses to these indicators can be formulated as follows:

$$L_{I_i,q}(I_i \mid \tau, \zeta_i, \alpha_i) = \sum_{k=1}^{5} x_{I_{i,q},k} \left(\frac{e^{\tau_{I_q,0} - \zeta_{iq}\alpha_i}}{1 + e^{\tau_{I_q,k} - \zeta_{iq}\alpha_i}} - \frac{e^{\tau_{I_q,k-1} - \zeta_{iq}\alpha_i}}{1 + e^{\tau_{I_q,k-1} - \zeta_{iq}\alpha_i}} \right) \tag{4.4}$$

where, $x_{I_{i,q},k} = 1$ if and only if participant *i* chooses *k* for the statement *q*. The τ parameters are thresholds, with the normalization that $\tau_{I_q,0} = -\infty$ and $\tau_{I_q,5} = +\infty$.

4.2. Class-membership model

The LCC model consists of estimating a class-membership model and a class-specific discrete choice model. The class-membership model determines the probability of belongingness of an individual to each class. In this study, it is hypothesized that the class-membership depends on the sociodemographic variables and the latent construct of mode-use habit. Let z_i be the vector representing sociodemographic characteristics and α_i^{hab} be the latent construct of habit. The following equation describes the class-membership function:

$$\lambda_{i,c} = \gamma_{0c} + \gamma_c z_i + \gamma_c^{hab} \alpha_i^{hab} + \varepsilon_{ic}, \qquad \varepsilon_{ic} \sim Gumbel(0, I) \tag{4.5}$$

where, λ_{ic} is the latent utility of individual *i* belonging to class *c*; γ_{0c}, γ_c, and γ_c^{hab} are the parameters to be estimated; and ε_{ic} is an error term assumed to be independent and identically distributed across individuals. Then, the probability of an individual *i* falling to a specific class *c* takes the form of multinomial logit structure and estimated as:

$$L_{i,c} = \frac{\exp\left(\gamma_{0c} + \gamma_c z_i + \gamma_c^{hab} \alpha_i^{hab}\right)}{\sum_c^C \exp\left(\gamma_{0c} + \gamma_c z_i + \gamma_c^{hab} \alpha_i^{hab}\right)} \tag{4.6}$$

4.3. Class-specific choice model

The class-specific utility function, explaining the choice of alternative *s* by an individual *i* given the choice task *t*, can be written as follows:

$$U_{s,i,t|c} = \beta_{0sc} + \beta_{sc}^X X_{sit} + \Lambda_c^\alpha \alpha_i + \varepsilon_{sit|c}, \quad \varepsilon_{sit|c} \sim Gumbel(0, I) \tag{4.7}$$

$$y_{s,i,t|c} = \begin{cases} 1, & \textit{if } U_{s,i,t|c} = \max_r U_{r,i,t,|c}, \ \forall r \in R, \ r \neq s \\ 0, & \textit{otherwise.} \end{cases} \tag{4.8}$$

where, $U_{sit|c}$ is a vector of class-specific utilities for an individual *i*; X_{sit} is the vector of alternative-specific attributes; $\beta_{0sc}, \beta_{sc}^X$ and Λ_c^α are vectors of class-specific parameters to be estimated; $\varepsilon_{sit|c}$ is an error term in the utility i.i.d. extreme value type 1 distributed. Thus, $L_{s,i,t|c}$ being the likelihood of an individual *i* choosing an alternative *s* for a given choice task *t*, conditional upon the individual *i* belongs to class *c* can be expressed as:

$$L_{s,i,t|c}\left(s \mid X_{sit}, \beta_{sc}^{X}, \alpha_i, \Lambda_c^{\alpha}\right) = \prod \frac{\exp\left(\beta_{0sc} + \beta_{sc}^{X} X_{sit} + \Lambda_c^{\alpha}\alpha_i + \varepsilon_{sit|c}\right)}{\sum_r \exp\left(\beta_{0rc} + \beta_{rc}^{X} X_{rit} + \Lambda_c^{\alpha}\alpha_i + \varepsilon_{rit|c}\right)} \tag{4.9}$$

And the unconditional probability of an individual i choosing alternative s for a given choice task t, integrating over number of latent classes C, is:

$$L_{s,i,t} = \sum_c^C L_{i,c} \prod_t^{T_i} L_{s,i,t|c} \tag{4.10}$$

Equation 4.10 accounts for both the class-membership probabilities and the choice probabilities within each class c.

The joint likelihood of the proposed integrated LCLV model, determining the probability of observing the alternative s, an individual i belonging to a latent-class c, and measurement indicator I_i can be estimated as the product of the different model components (Equation 4.1, Equation 4.2, Equation 4.4, Equation 4.6, and Equation 4.9). Equation 4.11 express the unconditional joint likelihood (non-closed form) as the integrals of the product of the likelihoods of different model components over the distribution of latent variables:

$$L_i\left(s, c_i, I_i\right) = \int_{\alpha_i} \begin{bmatrix} L_{s,i,t|c}\left(s \mid X_{sit}, \beta_{sc}^{X}, \alpha_i, \Lambda_c^{\alpha}\right) \; L_{i,c}\left(c_i \mid \gamma_c, z_i, \gamma_c^{hab}, \alpha_i^{hab}\right) \\ L_{I_i,q}(I_i \mid \tau, \zeta_i, \alpha_i) \; L_{\alpha_i}\left(\alpha_i \mid z_i, \Gamma\right) \end{bmatrix} d\alpha_i \tag{4.11}$$

where, $L_{\alpha_i}\left(\alpha_i \mid z_i, \Gamma\right)$ is the density of $N\left(\Gamma z_i, 1\right)$ implied to Equation 4.1.

The proposed model with all sorts of specifications was estimated using *Apollo* package in R environment (Hess and Palma, 2019). The model was estimated on a large dataset with 7101 choices across 726 individuals. A joint likelihood function mentioned in Equation 4.11, being multi-dimensional integrals with non-closed form, was estimated using the full information maximum simulated likelihood (MSL) estimator with 1000 'mlhs' draws per latent construct.

4.4. Willingness-to-pay analysis

Based on the proposed choice model, the WTP is analysed for the alternative-specific attributes. The value of WTP is typically obtained by taking a ratio of coefficient of the alternative attribute β_a to the coefficient of cost β_c:

$$WTP = -\frac{\beta_a}{\beta_c} \tag{4.12}$$

Since the calculated WTP (i.e., WTP) is based on the estimated choice model, it relies on the probability distribution of the model coefficient. Thus, it is desirable to estimate confidence intervals (CIs), in addition to the point estimates. For this study, the Delta method is used for calculating CIs, which is widely adopted to determine the standard error for a function of the fixed and random parameter estimates. More details can be found in (Bliemer and Rose, 2013; Scaccia et al., 2023). This method assumes that the maximum likelihood estimates (MLEs) of the coefficients and their ratios follow an asymptotic normal distribution. Using this method, the standard error (se) of WTP is approximated as:

$$\text{se}\,(WTP) = \frac{1}{\beta_{\mathrm{c}}}\sqrt{\mathrm{var}\left(\beta_a\right) + 2 \cdot WTP \cdot \mathrm{cov}\left(\beta_{\mathrm{c}}, \beta_a\right) + WTP^2 \cdot \mathrm{var}\left(\beta_{\mathrm{c}}\right)} \tag{4.13}$$

where, $\mathrm{var}\left(\beta_a\right)$ is variance of attribute coefficient, $\mathrm{var}\left(\beta_{\mathrm{c}}\right)$ is variance of cost coefficient, and $\mathrm{cov}\left(\beta_{\mathrm{c}}, \beta_a\right)$ is covariance between the two coefficients. The estimated $\text{se}\,(WTP)$ can be utilised to compute confidence intervals at the $(1 - \alpha)$ level as:

$$WTP \pm z_{\alpha/2}\,\text{se}\,(WTP) \tag{4.14}$$

where $z_{\alpha/2}$ represents the $100\left(1-\alpha/2\right)$th percentile of the standard normal density.

5. Model estimation and results

This section presents the modelling results of four different components of integrated LCLV – a) measurement models for latent constructs, b) structural models for latent constructs, c) class-membership model in LCCM, and d) class-specific discrete choice models. Readers may refer to Appendices 4.1 and 4.2 illustrating MNL model with SP attributes and 2-Class LCCM model with SP attributes without latent constructs.

5.1. Results of measurement models

The list of measurement items associated with the latent constructs is displayed in Table 3.2. Before estimating the measurement models with LCLV framework, an exploratory factor analysis (EFA) was conducted to extract the underlying latent constructs. Items with factor loadings greater than 0.5 were retained for the further confirmatory factor analysis (CFA) to confirm the factor structure obtained through EFA. Cronbach's alpha values for all the extracted latent constructs remain above 0.6 indicating inter consistency. Further, tests for convergent validity and discriminant validity were conducted to ensure that the latent constructs can be used for further analysis. The details of these analysis steps are available in Chapter 3. Table 4.5 shows the measurement models for the underlying latent constructs. All the estimated parameters (ζ_i) are significant at 90% or higher level reflecting the adequacy of the proposed ordered-logit models in mapping the relationship between latent constructs and associated measurement items.

Table 4.5 Parameter estimates (ζ_i) for measurement models

Latent constructs (α_i)	**Indicators** (I_i)	**Estimate** (ζ_i)	**Thresholds** (τ) **1**	**2**	**3**	**4**
Personal Innovativeness (PI)	PI1	3.165 (5.37)	5.374 (-4.96)	-5.566 (-18.39)	-4.959 (40.57)	-1.067 (4.38)
	PI2	2.259 (1.69)	-4.970 (-2.53)	-0.658 (-7.86)	1.879 (12.05)	5.653 (6.07)
	PI3	1.658 (7.82)	-2.770 (-7.22)	1.256 (13.71)	1.656 (7.59)	3.190 (4.19)
Environmental Awareness (EA)	EA1	2.226 (2.72)	-5.858 (-1.88)	-1.029 (-3.93)	1.365 (11.24)	5.836 (2.16)
	EA2	2.156 (10.75)	-6.472 (-6.21)	-2.362 (-13.12)	1.671 (14.27)	5.875 (3.13)
	EA3	1.265 (2.73)	-2.894 (-2.9)	-0.488 (-11.72)	1.219 (3.72)	3.486 (5.84)
Social Influence (SI)	SI1	1.654 (9.93)	-4.821 (-5.25)	-1.634 (-8.13)	2.379 (7.5)	5.097 (10.75)
	SI2	1.345 (13.18)	-5.247 (-8.62)	-2.020 (-11.72)	1.876 (12.76)	5.362 (9.79)
Scepticism (SC)	SC1	1.116 (10.25)	-4.557 (-2.19)	-2.372 (-8.72)	-0.039 (-12.18)	6.219 (3.04)
	SC2	1.898 (4.12)	-5.401 (-4.32)	-3.022 (-10.41)	1.290 (13.37)	4.972 (8.26)
	SC3	0.946 (9.32)	-3.064 (-4.56)	-0.370 (-9.22)	1.877 (13.13)	4.732 (5)
Perceived Risk (PR)	PR1	1.525 (12.89)	-4.771 (-9.51)	-1.236 (-3.05)	1.622 (10.72)	4.324 (3.22)
	PR2	1.699 (10.13)	-3.306 (-3.57)	-0.971 (-13.06)	0.282 (0.8)	3.396 (1.69)
	PR3	0.836 (8.66)	-2.126 (-12.87)	-1.520 (-10.55)	0.876 (1.8)	3.399 (2.28)
Perceived Usefulness (PU)	PU1	1.896 (1.81)	-6.039 (-6.99)	-2.879 (-6.07)	1.066 (7.33)	3.933 (5.51)
	PU2	1.116 (2.15)	-4.770 (-11.57)	0.081 (6.05)	2.368 (11.14)	5.743 (1.85)
	PU3	0.987 (10.22)	-5.170 (-3.77)	-3.686 (-1.57)	-0.972 (-4.42)	4.981 (12.29)
	PU4	2.336 (2.36)	-6.806 (-12.78)	-2.333 (-9.65)	1.486 (11.32)	3.923 (2.38)
	PU5	1.889 (8.87)	-3.569 (-13.89)	-1.534 (-10.87)	0.963 (1.3)	3.772 (7.12)
Mode-use Habit (HAB)	HAB1	2.670 (9.85)	-6.232 (-6.88)	-0.778 (-1.99)	0.098 (11.74)	5.336 (4.73)

HAB2	2.123 (7.72)	-5.147 (-11.89)	-3.852 (-5.02)	2.678 (1.42)	5.017 (6.58)
HAB3	1.763 (11.72)	-4.265 (-7.75)	-2.078 (-11.42)	0.648 (4.14)	3.736 (13.07)
HAB4	1.122 (8.56)	-3.229 (-1.43)	0.028 (2.46)	2.510 (6.03)	4.207 (13.79)
HAB5	2.367 (6.19)	-6.978 (-11.56)	-3.741 (-12.85)	2.712 (11.61)	8.212 (9.07)

Note: *t*-stats are in parentheses.

5.2. Results of structural models for latent constructs

Table 4.6 reports the results of structural model for the seven latent constructs, including mode-use habit. These results demonstrate the association between sociodemographic characteristics and latent constructs. Respondents aged between 18–34 group and 35–54 group exhibit higher personal innovativeness (PI) compared older respondents, which is also the case with graduate respondents relative to non-graduates. Even though the parameter estimates for the environmental awareness (EA) are significant for gender and age, the magnitudes seem lesser implying only a minor difference between males and females, and elders and youngers. Females and younger respondents (18–34 group) tend to feel more approved of their community/peers when they use SEMS, which is also true for graduate respondents. Females exhibit higher scepticism (SC) in terms of switching the commute mode, as are the graduates, elderly respondents, and full-time workers. Similarly, respondents with higher income (above 80k) and car ownership (two or more) show reluctance to shift their daily commute mode. The results for perceived risk (PR) reveal that females, full-time workers, and respondent with children in household perceive higher risk and reliability issues with SEMS compared to their respective counterparts. Interestingly, the coefficients for young and middle-age groups (vs. age above 55) are not significant in this case, who are otherwise more likely to take risk compared to older people. Young graduates with lower(/zero) car ownership tend to find SEMS more useful for their commute. It is interesting to note that full-time workers, who exhibit scepticism and higher perceived risk towards SEMS are also the one who find SEMS useful, which is a positive sign. The estimates for habit clearly present a similar behaviour to scepticism. Females, full-time workers with higher car ownership are more habitual to commute with their present transport mode, compared to younger respondents from middle income group (40k–80k). In summary, the directions of all significant parameter estimates are in line with expectations and previous travel behaviour studies.

Table 4.6 Parameter estimates (Γ) for the structural models.

Variable (z_i)	**Latent constructs (α_i)**						
	PI	**EA**	**SI**	**SC**	**PR**	**PU**	**HAB**
Female (vs. male)	-0.085 (-1.27)	**-0.008** **(-4.00)**	**0.234** **(1.91)**	**0.578** **(2.09)**	**0.374** **(2.11)**	-1.892 (-1.51)	**0.356** **(3.98)**

Age 18–34 (vs. age above 55)	**0.406** **(3.26)**	**0.019** **(2.11)**	**0.174** **(1.76)**	**-0.234** **(-4.18)**	-0.52 (-0.53)	**0.871** **(3.86)**	**-0.313** **(-2.04)**
Age 35–54 (vs. age above 55)	**0.286** **(3.27)**	**0.008** **(1.65)**	**0.092** **(2.09)**	0.278 (1.14)	-0.428 (-1.56)	0.667 (1.37)	-0.118 (-0.78)
Graduate (vs. non-graduate)	**0.399** **(3.1)**	0.395 (1.59)	**0.198** **(3.12)**	**0.175** **(1.79)**	**-0.086** **(-2.37)**	**0.400** **(175.24)**	0.168 (1.6)
Full time worker (binary with yes=1)	-	-	-	**0.174** **(3.23)**	**0.209** **(2.24)**	**0.118** **(2.3)**	**0.188** **(2.98)**
HH income under 40k (vs. above 80k)	-	-	-	**-0.126** **(-5.32)**	-0.091 (-0.49)	0.678 (0.87)	-0.159 (-0.85)
HH income 40k–80k (vs. above 80k)	-	-	-	**-0.114** **(-2.58)**	0.128 (1.02)	0.781 (0.59)	**-0.326** **(-3.00)**
Children in HH (binary with yes=1)	-	-	-	0.055 (0.31)	**0.372** **(2.23)**	-0.099 (-0.67)	-
Cars = 1 (vs. no car)	-	-	-	**0.083** **(2.04)**	0.675 (1.49)	**-0.118** **(-6.55)**	0.081 (0.38)
Cars = 2 or more (vs. no car)	-	-	-	**1.06** **(4.27)**	0.492 (1.58)	**-0.61** **(-16.13)**	**0.404** **(1.86)**

Note: *t*-stats are in parentheses; Bold indicates statistical significance at $p \leq 0.1$.

5.3. Results of class-membership model

To determine the appropriate number of latent classes, firstly, models with number of classes ranging from two to five were estimated. Looking to the extent of final model parameters and computation efficiency, basic models without latent variables were estimated for this purpose. To assess the goodness-of-fit of the estimated models, typical measures including Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC) were adopted, which weighs both model fit and parsimony. Additionally, consistent AIC (CAIC) is adopted which penalises the number of parameters in the model and favours more parsimonious models (Moors and Vermunt, 2007; Wedel and Kamakura, 1999). A general rule is to select the model with the lowest BIC, AIC and CAIC values. Table 4.7 reports the models attempted and associated goodness-of-fit measures. Clearly, the latent class model with three segments outperformed other configurations with lowest values of adopted criteria. However, in the full model estimation, size of the third segment was found to be only 0.14% (i.e., sample size = 1) which is difficult to interpret and not desirable. Hence, the final model with two classes was preferred looking to the second-lowest BIC value.

Table 4.7 Criteria for number of segments selection.

Model criteria	**Number of segments**				
	1 (MNL)	**2**	**3**	**4**	**5**
Number of parameters	60	131	202	273	344
LL-final	-6567.28	-6046.49	-5560.83	-5599.54	-6103.61
AIC	13254.56	12320.98	**11461.65**	11651.09	12895.22

CAIC	13425.61	12728.43	**12101.52**	12523.34	13875.88
BIC	13666.64	13103.78	**12628.99**	13202.96	13531.88
Rho-squared vs. observed shares	0.1836	0.2464	0.3069	0.3021	0.2392
Adj. Rho-squared vs. observed shares	0.177	0.2322	0.2857	0.2739	0.1964

Table 4.8 shows the parameter estimates for the class-membership model where Class 2 is considered as reference class. The model depicts the relevancy of several sociodemographic variables and mode-use habit in determining the belongingness of the respondents to a specific latent class. The parameters with statistical significance higher than 90% level were considered to characterise the observed latent segments. It is evident that Class 1 (60.89% of the sample) can be predominantly described by males, youngers, those with moderate household income range (40k–80k), lower car-ownership (1 or none), and importantly non-habitual individuals (with significant negative parameter estimate). The coefficient for middle-age group is positive, but not very strong, which depict that respondents in this age-group are possibly distributed over both the classes. On the other side, Class 2 (39.11% of the sample) comprises elderly female respondents from higher income (above 80k) and car-ownership (2 or more) groups, who tend to be habitual, particularly towards car use.

5.4. Results of class-specific choice model

In what follows, class-specific ICLV models were estimated by introducing the latent variables as continuous random parameters into the discrete choice part of the utility. Table 4.9 presents the class-specific discrete choice models explaining the effects of alternative-specific attributes (through SCE data), weather, and latent constructs. The ASCs for car (as main mode) and walking (as access/egress mode) were kept fixed in both the segments for identification purposes. The direction of associations of the significant parameters are broadly as expected. The values of final LL (vs. LL at zero) and pseudo-ρ^2 (0.586) depict the estimated model has sufficiently high explanatory power. Overall results reveal significant preference heterogeneity across the latent classes. To the objectives of this study, the focus would be limited to the estimates of SEMS modes and their comparison with estimates of car and public transport alternatives, and the comparison between two latent classes.

Table 4.8 Parameter estimates (γ_c) for the class-membership model.

Variables	Class 1 (size = 61%)			Class 2 (size = 39%)		
	Estimate ($\gamma_{c=1}$)	**S.E.**	***t*-stat**	**Estimate ($\gamma_{c=2}$)**	**S.E.**	***t*-stat**
Constant	**0.272**	**0.088**	**3.108**	Reference class		
Female (vs. male)	**-0.087**	**0.052**	**-1.673**			
Age 18–34 (vs. age above 55)	**0.151**	**0.088**	**1.712**			
Age 35–54 (vs. age above 55)	**0.029**	**0.010**	**3.053**			
Graduate (vs. non-graduate)	0.139	0.213	0.651			
Full time worker (binary with yes=1)	0.093	0.111	0.840			
HH income under 40k (vs. above 80k)	-0.121	0.339	-0.357			
HH income 40k–80k (vs. above 80k)	**0.392**	**0.210**	**1.868**			
Children in HH (binary with yes=1)	0.019	0.193	0.099			
Cars = 1 (vs. no car)	**0.044**	**0.009**	**4.786**			
Cars = 2 or more (vs. no car)	**-0.198**	**0.042**	**-4.714**			
Mode-use habit	**-0.284**	**0.097**	**-2.928**			

Note: Bold indicates statistical significance at $p \leq 0.1$.

Table 4.9 Parameter estimates (β_c) for the class-specific choice models.

Variables	Class 1 (size = 61%)			Class 2 (size = 39%)		
	Estimate ($\beta_{c=1}$)	**SE**	**t**	**Estimate ($\beta_{c=2}$)**	**SE**	**t**
ASCs						
Car	Reference			Reference		
Public transport	**0.341**	0.141	2.42	**-1.441**	0.711	-2.03
E-carsharing (main)	-0.323	0.588	-0.55	**-2.574**	0.576	-4.47
E-bikesharing (main)	**-4.107**	0.958	-4.28	**-16.831**	4.280	-3.93
E-scootersharing (main)	**-1.544**	0.410	-3.76	**-10.902**	6.055	-1.80
E-bikesharing (access/egress)	-1.885	1.506	-1.25	**-2.774**	0.650	-4.27
E-scootersharing (access/egress)	**-4.535**	0.801	-5.66	**-5.458**	1.808	-3.02

Walking (access/egress)	Reference			Reference		
In-vehicle time (min)						
Car	**-0.104**	0.019	-5.47	**-0.067**	0.026	-2.61
Public transport	**-0.121**	0.012	-10.08	**-0.133**	0.020	-6.65
E-carsharing (main)	**-0.093**	0.021	-4.43	**-0.138**	0.025	-5.61
E-bikesharing (main)	**-0.099**	0.032	-3.09	**-0.554**	0.278	-1.99
E-scootersharing (main)	-0.015	0.045	-0.33	**-0.427**	0.124	-3.45
E-bikesharing (access/egress)	-0.027	0.076	-0.36	-0.046	0.132	-0.35
E-scootersharing (access/egress)	**-0.241**	0.070	-3.42	**-0.348**	0.125	-2.78
Access time						
Public transport	**-0.093**	0.018	-5.14	-0.009	0.033	-0.27
E-carsharing (main)	-0.033	0.028	-1.18	**-0.078**	0.024	-3.27
E-bikesharing (main)	**0.076**	0.029	2.57	**-1.024**	0.358	-2.86
E-scootersharing (main)	**-0.135**	0.044	-3.07	**-0.359**	0.128	-2.80
Egress time						
Car	**-0.058**	0.018	-3.22	**-0.070**	0.027	-2.59
Public transport	**-0.060**	0.017	-3.53	**-0.249**	0.038	-6.60
E-carsharing (main)	**-0.134**	0.030	-4.47	**-0.132**	0.026	-5.14
E-bikesharing (main)	**-0.158**	0.031	-5.10	**-0.512**	0.189	-2.71
E-scootersharing (main)	**-0.362**	0.054	-6.65	-0.131	0.096	-1.36
Waiting time						
Public transport	**-0.191**	0.019	-9.90	**-0.046**	0.027	-1.70
E-carsharing (main)	0.054	0.042	1.29	-0.056	0.038	-1.47
E-bikesharing (main)	**-0.064**	0.012	-5.33	-0.813	0.574	-1.42
E-scootersharing (main)	-0.191	0.168	-1.14	**-1.689**	0.648	-2.61
E-bikesharing (access/egress)	-0.074	0.092	-0.80	**-0.674**	0.175	-3.86
E-scootersharing (access/egress)	**0.167**	0.092	1.82	0.033	0.173	0.19
Walking time						
E-bikesharing (access/egress)	**-0.043**	0.022	-1.94	0.061	0.098	0.62
E-scootersharing (access/egress)	**-0.067**	0.038	-1.76	0.071	0.100	0.71
Walking (access/egress)	**-0.072**	0.021	-3.40	**-0.381**	0.077	-4.98
Travel cost						
Car	**-0.492**	0.230	-2.14	-0.184	0.181	-1.02
Public transport	**-0.458**	0.262	-1.75	0.123	0.148	0.83
E-carsharing (main)	**-0.301**	0.057	-5.28	**-0.211**	0.049	-4.32
E-bikesharing (main)	**-0.613**	0.099	-6.20	**-1.660**	0.635	-2.61
E-scootersharing (main)	**-0.401**	0.126	-3.18	**-0.648**	0.342	-1.89
E-bikesharing (access/egress)	**-0.662**	0.266	-2.49	**-1.449**	0.494	-2.93
E-scootersharing (access/egress)	-0.034	0.267	-0.13	-0.455	0.478	-0.95
Parking cost						

Car	**-0.588**	0.016	-37.22	**-0.262**	0.017	-15.41
Availability (%)						
E-carsharing (main)	**0.011**	0.004	2.75	**0.004**	0.000	8.78
E-bikesharing (main)	**0.018**	0.010	1.80	0.034	0.037	0.92
E-scootersharing (main)	-0.007	0.015	-0.48	**-0.005**	0.002	-2.01
E-bikesharing (access/egress)	**0.021**	0.004	5.15	**0.056**	0.010	5.60
E-scootersharing (access/egress)	**0.036**	0.005	7.44	**0.041**	0.007	5.86
Rainy weather (vs. sunny weather)						
Car	-1.071	0.874	-1.23	-1.051	0.662	-1.59
Public transport	**-0.298**	0.137	-2.18	**-0.483**	0.225	-2.14
E-carsharing (main)	**-0.866**	0.490	-1.77	**-1.119**	0.309	-3.62
E-bikesharing (main)	**-1.003**	0.308	-3.26	**-3.686**	0.311	-11.87
E-scootersharing (main)	**-1.421**	0.836	-1.70	**-1.216**	0.309	-3.94
E-bikesharing (access/egress)	**-0.787**	0.388	-2.03	**-1.249**	0.137	-9.12
E-scootersharing (access/egress)	0.083	0.066	1.26	**-0.785**	0.299	-2.63
Walking (access/egress)	**0.704**	0.403	1.75	**2.034**	0.546	3.73
Temperature ≤10° C (vs. >10° C)						
Car	-0.218	0.362	-0.60	**1.009**	0.588	1.72
Public transport	**-0.103**	0.052	-1.97	**-1.113**	0.672	-1.66
E-carsharing (main)	**0.056**	0.028	2.02	**0.935**	0.525	1.78
E-bikesharing (main)	**0.021**	0.009	2.33	**-1.946**	0.523	-3.72
E-scootersharing (main)	0.298	0.274	1.09	**-1.111**	0.525	-2.12
E-bikesharing (access/egress)	**-0.115**	0.045	-2.56	**-0.321**	0.165	-1.94
E-scootersharing (access/egress)	-0.002	0.906	0.00	**-0.849**	0.175	-4.86
Walking (access/egress)	0.119	0.092	1.29	**0.528**	0.164	3.22
Latent constructs						
Personal innovativeness (PI)	**1.316**	0.387	3.40	**0.548**	0.256	2.14
Environmental awareness (EA)	**0.335**	0.202	1.66	0.222	0.372	0.60
Social influence (SI)	0.873	0.603	1.45	0.651	0.439	1.48
Scepticism (SC)	0.391	0.246	1.59	**-0.139**	0.023	-6.04
Perceived risk (PR)	**-0.412**	0.232	-1.78	**-0.727**	0.307	-2.37
Perceived usefullness (PU)	**0.973**	0.192	5.07	**-0.087**	0.032	-2.72
Number of respondents	726					
Number of observations	7101					
Number of model parameters	355					
LL at zero	-28465.51					
LL at model convergence	-9630.59					
Adj. pseudo ρ^2	0.586					

Note: Bold indicates statistical significance at $p \leq 0.1$.

The ASCs in both models are mostly significant, which means that everything being equal, respondents tend to avoid using SEMS modes for the commute. However, the associated estimates for Class 2 are quite higher compared to Class 1, indicating higher reluctance of individuals belonging to Class 2 conformed to their habitual and other characteristics. Also, it is interesting to note that individuals in Class 1 are more public transport friendly (positive significant coefficient) than those in Class 2 (negative significant coefficient). In a similar fashion, Class 2 shows higher sensitivity to in-vehicle travel time for SEMS modes, both for main-haul trip as well as access/egress trips. Further, being car friendly individuals, they exhibit higher preference for shared e-car compared to micro-modes. When comparing access time for public transport and SEMS for main-haul trip, Class 2 shows higher sensitivity than Class 1. This sensitivity is higher for e-scooter in Class 1 and e-bike in Class 2. The coefficient for e-bike positive for Class 1, which is very opposite to the Class 2, though the magnitude is much lower in case of Class 1. As a whole, individuals in Class 1 tend to prefer e-bikes with increased access time, while those in Class 2 still prefer e-car over other SEMS modes (looking to the smallest negative coefficient with small magnitude). In case of egress time to destination, the magnitudes of coefficients are much lesser for car and public transport compared to SEMS modes for Class 1, which shows higher propensity towards traditional modes. While for Class 2, the associated sensitivity is lowest for car, followed by shared e-car and public transport, and highest for e-bike. With increased probability of immediate availability of SEMS modes, the use tends to be higher, though the strengths of all significant associations are very less. The higher waiting time costs more to the public transport's utility compared to e-bike for main-haul trip in Class 1. Interestingly, this relationship is positive in case of e-scooter as access/egress mode to public transport, i.e., waiting time does not influence the negative probability of e-scooter choice. For Class 2, increased waiting time significantly decreases the probability of using e-scooter for shorter trips, as is the case with e-bike for access/egress trips. In terms of walking to SEMS station for access/egress trips to public transport, no significant difference found between e-bike and e-scooter for Class 1. The individuals in Class 2 are less inclined to walking compared to Class 1.

The signs of all travel cost coefficients for both the classes are negative. Class 1 is more sensitive to cost of e-car compared to Class 2, while the opposite is true for e-scooter and e-bike. In case of access/egress trips, the coefficients are significant only for bike sharing in both the classes with Class 2 being more sensitive compared to Class 1. Although non-significant, the positive sign of public transport cost coefficient for Class 2 needs attention. While this class is habitual, it is possible that individuals in this class possess transit pass and have less to no effect of increased transit pass cost. The coefficients for parking cost of private cars are significant for both classes with negative direction, though the sensitivity is higher for Class 1.

The estimates for weather are negative for all main-haul modes except car. In comparison, individuals tend to prefer public transport with walking as access/egress in rainy weather. However, this relationship should be confirmed with the effects on car use, which are not significant in this study. Amongst SEMS modes, the coefficients are lowest for e-car, which is logical. Contrary to the other results, estimates for temperature show that individuals in Class 1 tend to prefer SEMS modes over public transport, though the intensity is not much higher.

Further, they are less inclined to use e-bike for access/egress to public transport. For individuals in Class 2, private cars and shared e-cars are preferred over other modes for main-haul trips, while SEMS modes are less favoured compared to walking for access/egress trips.

Lastly, a few psychometric factors also significantly affect the SEMS choice behaviour. Both classes show significant effect of personal innovativeness with Class 1 exhibit nearly two time the sensitivity than Class 2. Environmental awareness has significant positive impact only to the Class 1 individuals. This study did not find significant effects of social influence SEMS adoption unlike other studies investigating intentions (Dill et al., 2022; Kaplan et al., 2018). Class 2 individuals seem sceptical to change their current mode of transport (primarily car) with negative effects of latent construct scepticism (SC). Both classes positively perceive the risk associated with the usage of SEMS (being negative estimated coefficients) where Class 2 seem higher sensitive to their risk perception. Interestingly, only Class 1 individuals found SEMS modes useful for their commute trips, while Class 2 exhibit significant negative association with PU, though the association is not so strong (β = -0.087).

6. Discussion

This section discusses the results obtained specifically in context of SEMS modes, respondents' willingness-to-pay (WTP) for different trip time components and observed substitution patterns. Further, practical policy implications are provided to improve the sustainability of the transport system.

Overall empirical results support the model proposed in this study and the proposition regarding the effects of habit in latent class segmentation and adoption of SEMS. Results depict that the Class 1 – composed of males, young and middle-age groups, those with moderate household income, lower car-ownership, and non-habitual individuals – may find SEMS modes an attractive solution for commute trips, which is in line with previous studies (Aguilera-García et al., 2020b; Bai and Jiao, 2020; Campbell et al., 2016; Curtale et al., 2021b; Curtale and Liao, 2023b; Prieto et al., 2017). These individuals have higher preference towards shared e-bikes and e-scooters than to e-cars when compared with Class 2 individuals. Class 2 individuals seem more car-friendly and tend to prefer shared e-cars over e-bikes and e-scooters (comparatively lower sensitivity towards shared e-car service attributes). This group is composed of females, older age groups, high income earners with higher car ownership, and habitual to their current commute mode (primarily car). Therefore, it can be stated that the car-friendly individuals tend to prefer shared e-cars and public transport-friendly individuals tend to prefer e-bikes and e-scooters, where the former show higher time and cost sensitivity to e-bikes and e-scooters and the later show higher sensitivity to shared e-cars attributes. This study did not find significant difference between graduated and non-graduated individuals' preferences as in the studies by (Curtale and Liao, 2023b; Kopp et al., 2015). Further, they found that high income earners are potential users of SEMS, which is in contrast to what has been found in this study. Possible reason can be the effects of habit and simultaneous effects of higher car ownership in latent class segmentation which was not explored previously.

Results show that some of the included psychometric factors are also significant in determining adoption of SEMS modes amongst commuters. Comparatively, personal innovativeness and perceived usefulness have higher positive influence on SEMS adoption for non-habitual individuals. Further, they possess lower risk propensity in using SEMS modes compared to habitual individuals. When it comes to rainy weather, respondents exhibit high reluctance towards SEMS modes relative to public transport, while no significant effects found on car-use, which is logical in broader sense. Additionally, they prefer to walk over SEMS modes for access/egress while using public transport. That means people tend to prefer to walk directly to transit station rather than accessing SEMS station during adverse weather conditions. Similar is true for cold weather as well. Though, shared e-cars and shared e-bikes (for short trips) are still preferable during low temperatures.

6.1. Willingness-to-pay analysis

Based upon the coefficients of various time components and travel cost, willingness to pay (WTP) to save a minute of time was investigated. The general procedure is to divide coefficient of time by that of the travel cost. Table 4.10 reports the calculated WTP for each alternative in the choice model. It also reports the 95% level confidence intervals ($z_{\alpha/2} = z_{0.025} \approx 1.96$) estimated using the Delta method. The corresponding values are in bold where both time and cost coefficients are significant in the choice model. There is wide heterogeneity in WTP values for different time components. Overall, Class 2 has higher WTP values compared to Class 1. Within Class 1, shared e-car has the highest WTP (0.31 £/min) for in-vehicle time, while shared e-scooter has the highest WTP for access time (0.34 £/min) and egress time (0.90 £/min). Shared e-bike has the lowest WTP for all time components in Class 1. In case of access/egress, respondents are willing to pay much smaller price for shared e-bike (~4 £/hr). In Class 2, shared e-car and shared e-scooter have similar and the higher WTP. For access time to SEMS station, shared e-bike has highest WTP (0.62 £/min), followed by shared e-scooter (0.55 £/min) and shared e-car (0.37 £/min). While in case of egress time, shared e-car has the highest WTP (0.63 £/min) compared to other modes. The WTP for waiting time for shared e-scooter is exceptionally high for Class 2. While these values are more or less in line with the WTP found in previous studies in Europe (Baek et al., 2021; Krauss et al., 2022; Wardman et al., 2016), some are extremely high, such as for waiting time for shared e-scooter (156 £/hr) in Class 2 and egress time for e-scooters (54 £/hr) in Class 1, which needs further investigation.

While the point estimates of WTP provides approximation, it may not necessarily reflect the uncertainty in the estimate (which occurs as the estimated coefficients follow a specific probability distribution). Therefore, the derived CIs provide crucial insights into the stability and reliability of the estimates. When CI is narrow (e.g., the in-vehicle time for private car in Class 1), the estimate is more robust and stable. In contrast, some estimates come with wide CIs (e.g., in-vehicle time for shared e-scooter (A/E) with CI of [-99.97, 114.15]), which indicate a high degree of uncertainty. Though in the derived results, all CIs associated with bold values are relatively narrower indicating low variability in how respondents perceive that particular mode's time value.

Table 4.10 Willingness-to-pay for time components (£/min).

Attribute	Private car	Public transport	Shared e-car	Shared e-bike		Shared e-scooter	
				Main	A/E	Main	A/E
Class 1							
In-vehicle time	**0.21** [0.09, 0.32]	**0.26** [0.12, 0.41]	**0.31** [0.17, 0.45]	**0.16** [0.04, 0.28]	0.04 [-0.17, 0.25]	0.04 [-0.18, 0.26]	7.09 [-99.97, 114.15]
Access time		**0.20** [0.04, 0.36]	0.11 [-0.08, 0.30]	**-0.12** [-0.22, -0.02]		**0.34** [0.01, 0.67]	
Egress time	**0.12** [0.01, 0.23]	**0.13** [0.02, 0.24]	**0.45** [0.20, 0.70]	**0.26** [0.11, 0.40]		**0.90** [0.22, 1.57]	
Waiting time		**0.42** [0.15, 0.69]	-0.18 [-0.49, 0.13]	**0.10** [-0.27, 0.47]	0.11 [-0.17, 0.39]	0.48 [-0.29, 1.25]	-4.91 [-80.30, 70.48]
Walking time					**0.06** [-0.07, 0.19]		1.96 [-27.83, 31.75]
Class 2							
In-vehicle time	0.36 [-0.40, 1.12]	-1.08 [-5.73, 3.57]	**0.65** [0.33, 0.97]	**0.33** [0.06, 0.60]	0.03 [-0.14, 0.20]	**0.66** [-0.08, 1.40]	0.77 [-0.62, 2.16]
Access time		-0.07 [-0.62, 0.48]	**0.37** [0.08, 0.66]	**0.62** [-0.21, 1.45]		**0.55** [-0.15, 1.25]	
Egress time	0.38 [-0.59, 1.35]	-2.02 [-10.47, 6.43]	**0.63** [0.27, 0.99]	**0.31** [0.12, 0.50]		**0.20** [-0.19, 0.57]	
Waiting time		-0.37 [-1.93, 1.19]	0.27 [-0.09, 0.63]	0.49 [-0.07, 1.05]	**0.47** [0.06, 0.88]	**2.61** [-0.91, 6.13]	-0.07 [-0.84, 0.70]
Walking time					-0.04 [-0.18, 0.10]		-0.16 [-0.66, 0.34]

Note: 1) Bold values indicate that the corresponding attribute coefficient and cost coefficient are both significant in choice model; 2) 95% confidence intervals are shown in parentheses.

It is important to note that when a CI includes zero – for example, in access time of shared e-bike for Class 2 with an estimate of CI [-0.21, 1.45] – the effect can be statistically indistinguishable from zero at conventional significance levels as it spans on both sides of zero. This suggests that its value is highly heterogenous amongst respondents. The fact that some travel time components yield significant estimates (their CIs lie entirely above or below zero) while others do not, emphasizes that not all time components are perceived or valued uniformly across different modes and latent classes. In essence, when using these results to inform policy (e.g., determining fare subsidies), the precision indicated by the CI is critical. The parameters with significant and narrower intervals yields more confidence in understanding the economic trade-offs that the travellers are willing to make between time savings and cost.

6.2. Mode substitution

To investigate the potential substitution patterns after introducing SEMS modes, the estimated results were further simulated. The attribute values in SC experiment settings (explained in Section 3.1) were set to the middle level (except for weather and temperature), which characterises the average conditions of the stated alternatives. Then, the originally estimated choice model (as in Table 4.9) was applied for the individuals whose current most frequent modes of commute are either private car or public transport. Please note that this analysis for limited to main-haul trip as the substitution for access-egress trips were not in the scope of this chapter. Table 4.11 presents the observed substitution pattern under average conditions. To get more detailed insights, these results were further bifurcated to short trips and long trips as was presented in SC experiments. The results are mixed from sustainability point of view. While noticeable shift is observed from private car to SEMS modes and also towards public transport, similar is the case with public transport, which has a lower environmental impact than the SEMS modes (Luo et al., 2019; Reck et al., 2022). For shorter trips, car users have slightly higher preference towards shared e-car than public transport, possibly due to its comfort and convenience over public transport. Current public transport users seem more attracted towards shared e-bike and similar amount of shift is observed from public transport to private car as well. Overall, the observed substitution is nearly identical for private car (26%) and public transport (24%). Also, in case of long trips, major substitution is interchangeably between private car and public transport modes. Public transport users have slightly higher shift towards shared e-car and overall (4% more than private car). A shift from car to public transport can be the result of increased parking cost (negative coefficients in both classes) and may possibly come from individuals who do not perceive shared modes as the immediate alternatives to private cars. An opposite explanation can be made in regard to shift from public transport to car.

Table 4.11 Simulated results for mode substitution pattern.

Current mode	Percentage distribution				
	Private car	**Public transport**	**Shared e-car**	**Shared e-bike**	**Shared e-scooter**
Full sample					

Private car	63.47%	18.06%	11.61%	4.43%	2.43%
Public transport	18.65%	62.39%	8.36%	8.05%	2.55%
Short-trips					
Private car	61.62%	12.45%	14.26%	7.53%	4.14%
Public transport	13.15%	62.60%	7.98%	12.36%	3.91%
Long-trips					
Private car	66.10%	26.07%	7.83%	-	-
Public transport	28.95%	61.99%	9.06%	-	-

6.3. Policy interventions

The findings of this study provide several key insights for transport planners, policymakers and mobility operators on how SEMS can address the existing challenges in urban transport systems. Results suggest that SEMS modes, specifically, shared e-car has the potential to substitute private car trips for commute. According to Section 5.3, most car-friendly commuters are habitual, high-income earners with higher car ownership. Therefore, it is important to frame push-and-pull strategies that may appear to uptake the SEMS usage. This may include initially subsidised prices with reduced access/egress time through denser SEMS network in related areas, which can stimulate the SEMS usage. Breaking habitual behaviour is equally important in this regard – launching targeted awareness/marketing campaigns that highlight the economic, environmental, societal, and convenience benefits of SEMS can challenge the entrenched perceptions towards car dependency, risks, safety and reliability. Further, offering time limited discounts or free trials of SEMS modes encourage the commuters to testify new modes that my help building new habits of using SEMS modes. The development of habits is influenced by repeated positive experiences with SEMS, such as convenience, reliability, and cost-effectiveness. Over time, these experiences reinforce a habitual association, making SMES an automatic choice for specific contexts.

From planners and operators' position, it is imperative to maintain reliability and lower waiting time for SEMS modes by ensuring higher vehicle availability percentage and efficient demand-based relocation strategies. This can be achieved through continuous monitoring and evaluation mechanism by leveraging real-time data from SEMS operations to track usage pattern, identify gaps and pain points (through user feedback), and optimize resource allocation. Involving local communities in the planning and implementation of SEMS networks can address specific mobility challenges and build trust. Certain push (or hard) measures comprise restrictions for private cars in inner city areas (e.g., CBDs) along with provisions of reliable SEMS options and reallocating private car parking spaces for SEMS hubs can restrict the private car movement in these areas. Establishment of employer partnership to provide subsidised SEMS membership for daily car-based commuters and/or parking restrictions for private vehicles at workplaces may prove to be effective strategy. To cater with the perceived risks and safety, particularly for micro-mobility options, it is crucial to invest in dedicated infrastructure, such as protected bike lanes (separate from pedestrian paths) and well-lit SEMS stations, in order to enhance user confidence.

Addressing an unintended substitution from already sustainable transport modes, such as public transport in this study, should be imperative while developing strategical framework. It is important to maintain the attractiveness of public transport modes to avoid large substitution from this segment. Since SEMS is also more attractive to relatively price sensitive, medium-income earners with lower private car ownership, emphasize should be on integration over competition for this community to ensure that both modes work collaboratively. Providing last-mile solution through SEMS with integrated fare structure, particularly in areas with sparse public transport network (generally in suburb areas where such community resides), can complement the public transport usage. Collaborative partnership between public transport and SEMS operators (e.g., introducing MaaS bundles) is key strategy to regulate the usage pattern through data sharing and minimize substitution risks. While public transport is generally more effective for medium-to-long distance trips, dynamic pricing of SEMS modes to make it relatively less cost-effective than public transport can sustain the public transport usage. For suburb areas, introducing gamification or rewards programs when commuters use public transport complemented by SEMS for last-mile connectivity for longer commute can prove effective strategy to restrict the private car usage.

7. Conclusions

This study provides a comprehensive understanding of commuters' travel preferences when they have the availability of smart mobility solutions like SEMS that includes multiple alternatives such as e-car, e-bike, and e-scooter. This study contributes to extant literature by implementing an integrated LCLV modelling approach to leverage the advantages of LCCM and ICLV frameworks, enabling nuanced evaluation of heterogenous user groups. Since the commute mode choice behaviour is habitual in nature, a role of mode-use habit in addition to the sociodemographic characteristics is studied in understanding the discrete preference heterogeneity in choice behaviour through latent class segmentation. This study found significant moderating role of habit in characterising commuters' behaviour and how it is associated with their socio-economic characteristics. Further, the effects of psychometric factors such as environmental perception, innovativeness, perceived risk and usefulness, and alternative-specific stated choice attributes were investigated through ICLV-based discrete choice model framework. The results revealed that younger, non-habitual individuals with moderate incomes and lower car ownership showed higher preferences for SEMS modes, particularly shared e-bikes and e-scooters. On the other hand, older, habitual individuals with higher incomes and car ownership exhibited a stronger preference for private cars and shared e-cars. The WTP analysis yields key insights on the economic trade-offs that travellers may willing to make between time savings and associated cost. The analysis also identified key substitution patterns, such as shifts from private cars to SEMS and public transport, as well as unintended substitution from public transport to SEMS. Therefore, a balanced approach that integrates SEMS into broader urban mobility ecosystem through business-oriented (for operators) and goal-oriented (for sustainability) policies is imperative for creating cohesive and efficient yet sustainable urban transport.

There are some limitations of this study, which can be incorporated in relevant future studies. The current study is limited to commute trips performed frequently using either private cars or public transport. Similar studies in future can apply the current framework to different trip purposes like shopping, leisure, etc. Besides, the investigation with more comprehensive set of alternatives including personal bikes, mopeds, and ridesharing (e.g., using car as passenger) that might be used for commuting is due in future. This may provide more comprehensive understanding on the realistic potential impacts of SEMS modes, which might be overestimated here. While the substitution of public transport is analysed in this chapter, future study should also target the complementarity of SEMS modes with public transport, especially for long-distance trips. Since this study is relied upon the stated preference data, possibility of hypothetical biases and autocorrelation issues cannot be neglected. Hence, incorporating revealed preference data from SEMS usage logs and public transport systems can validate and enhance stated preference findings. In WTP analysis can be further expanded by comparing the results of Delta method with other available approaches such as Fieller method, Likelihood ratio test inversion method and Krinsky and Robb method. It might be fruitful to investigate the variability in WTP estimates with respect to sample size, variability in travel patterns (such single-mode and multimodal travel) and service improvements. Future research should also explore longitudinal data to capture travel behaviour change over time, including the effects of habit formation or breaking in context of SEMS. While the current study is limited to intracity commute, it would be interesting to examine the role of SEMS modes as last mile connectors in inter-city commute. Lastly, the study was conducted in selected English cities, and it would be worthwhile to delve into transferability of the implications to other regions and countries with differing transport systems and cultural contexts.

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Appendix to Chapter 4

Appendix 4.1. Parameter estimates for the MNL model on SP attributes

Variable (z_i)	**Estimate**	**SE**	**t**
ASCs			
Car	Reference		
Public transport	-0.359	0.305	-1.177
E-carsharing (main)	-0.421	0.364	-1.157
E-bikesharing (main)	-2.446	0.848	-2.884
E-scootersharing (main)	-1.227	1.334	-0.920
E-bikesharing (access/egress)	-1.334	0.427	-3.124
E-scootersharing (access/egress)	-4.739	0.668	-7.094
Walking (access/egress)	Reference		
In-vehicle time (min)			
Car	-0.068	0.013	-5.313
Public transport	-0.108	0.009	-12.000
E-carsharing (main)	-0.101	0.013	-7.594
E-bikesharing (main)	-0.075	0.029	-2.586
E-scootersharing (main)	-0.098	0.038	-2.579
E-bikesharing (access/egress)	-0.010	0.050	-0.196
E-scootersharing (access/egress)	-0.218	0.056	-3.893
Access time			
Public transport	-0.038	0.012	-3.167
E-carsharing (main)	-0.060	0.017	-3.529
E-bikesharing (main)	0.017	0.026	0.664
E-scootersharing (main)	-0.192	0.038	-5.050
Egress time			
Car	-0.047	0.013	-3.615
Public transport	-0.082	0.012	-6.693
E-carsharing (main)	-0.144	0.018	-8.000
E-bikesharing (main)	-0.105	0.028	-3.791
E-scootersharing (main)	-0.269	0.041	-6.577
Waiting time			
Public transport	-0.097	0.013	-7.760
E-carsharing (main)	-0.036	0.027	-1.343
E-bikesharing (main)	-0.154	0.109	-1.417
E-scootersharing (main)	-0.397	0.155	-2.561
E-bikesharing (access/egress)	-0.172	0.616	-0.279
E-scootersharing (access/egress)	0.209	0.072	2.901

Walking time			
E-bikesharing (access/egress)	-0.001	0.026	-0.032
E-scootersharing (access/egress)	0.021	0.029	0.724
Walking (access/egress)	-0.085	0.016	-5.294
Travel cost			
Car	-0.250	0.121	-2.066
Public transport	-0.111	0.108	-1.029
E-carsharing (main)	-0.236	0.034	-6.938
E-bikesharing (main)	-0.651	0.087	-7.478
E-scootersharing (main)	-0.183	0.103	-1.777
E-bikesharing (access/egress)	-0.427	0.177	-2.412
E-scootersharing (access/egress)	-0.353	0.211	-1.673
Parking cost			
Car	-0.255	0.009	-28.333
Availability (%)			
E-carsharing (main)	0.005	0.003	1.621
E-bikesharing (main)	0.006	0.009	0.682
E-scootersharing (main)	-0.025	0.013	-2.000
E-bikesharing (access/egress)	0.016	0.003	5.483
E-scootersharing (access/egress)	0.038	0.004	10.243
Rainy weather (vs. sunny weather)			
Car	-0.656	0.523	-1.254
Public transport	-0.353	0.042	-8.435
E-carsharing (main)	-0.684	0.199	-3.446
E-bikesharing (main)	-0.808	0.442	-1.830
E-scootersharing (main)	-0.883	0.596	-1.480
E-bikesharing (access/egress)	-0.590	0.290	-2.038
E-scootersharing (access/egress)	-0.062	0.072	-0.855
Walking (access/egress)	0.652	0.434	1.503
Temperature ≤10° C (vs. >10° C)			
Car	-0.208	0.323	-0.645
Public transport	-0.149	0.087	-1.716
E-carsharing (main)	0.023	0.012	1.812
E-bikesharing (main)	0.433	0.112	3.856
E-scootersharing (main)	-0.054	0.112	-0.483
E-bikesharing (access/egress)	-0.360	0.187	-1.929
E-scootersharing (access/egress)	0.216	0.372	0.580
Walking (access/egress)	0.144	0.158	0.913

LL(0): -8044.23; LL(model): -6567.28; No. of parameters: 60; adj. rho-squared: 0.177.

Appendix 4.2. Parameter estimates for the 2-class LCCM model without latent variables.

Table: Class-membership model.

Variables	Class 1 (size = 35%)			Class 2 (size = 65%)		
	Estimate	SE	t	Estimate	SE	t
Constant	-0.927	0.120	-7.754	Reference class		
Female (vs. male)	0.448	0.121	3.718			
Age 18–34 (vs. age above 55)	-0.117	0.067	-1.756			
Age 35–54 (vs. age above 55)	-0.025	0.082	-0.302			
HH income under 40k (vs. above 80k)	0.153	0.131	1.172			
HH income 40k–80k (vs. above 80k)	0.245	0.056	4.365			
Cars = 1 (vs. no car)	-0.369	0.079	-4.659			
Cars = 2 or more (vs. no car)	-2.00E-04	0.086	-0.002			
Bikes = 1 (vs. no bike)	0.223	0.157	1.424			
Bikes = 2 or more (vs. no bike)	-0.048	0.103	-0.467			

Table: Class-specific choice models.

Variables	Class 1 (size = 35%)			Class 2 (size = 65%)		
	Estimate	SE	t	Estimate	SE	t
ASCs						
Car	Reference			Reference		
Public transport	0.939	9.758	0.096	-1.247	0.588	-2.122
E-carsharing (main)	-1.842	0.675	-2.730	-1.856	1.256	-1.478
E-bikesharing (main)	-0.728	1.135	-0.642	-2.378	1.333	-1.784
E-scootersharing (main)	-2.964	3.132	-0.946	-2.115	0.228	-9.285
E-bikesharing (access/egress)	-0.920	2.095	-0.439	-0.989	0.390	-2.538
E-scootersharing (access/egress)	-2.271	0.896	-2.534	-2.335	1.334	-1.751
Walking (access/egress)	Reference			Reference		
In-vehicle time (min)						
Car	-0.769	0.859	-0.895	-0.556	0.978	-0.569
Public transport	-1.112	0.634	-1.755	-1.029	0.436	-2.363
E-carsharing (main)	-2.997	1.300	-2.306	-1.192	0.870	-1.370
E-bikesharing (main)	-3.075	3.066	-1.003	-9.246	3.112	-2.971
E-scootersharing (main)	-1.812	0.706	-2.567	-2.326	0.717	-3.243
E-bikesharing (access/egress)	1.289	0.635	2.030	-0.864	0.399	-2.163
E-scootersharing (access/egress)	-2.092	1.075	-1.946	-1.017	0.532	-1.911
Access time						
Public transport	-2.634	0.085	-31.096	-0.464	0.061	-7.575
E-carsharing (main)	-0.774	0.100	-7.712	-1.261	0.137	-9.204

E-bikesharing (main)	-0.468	0.071	-6.615	-1.624	0.166	-9.796
E-scootersharing (main)	-0.854	0.105	-8.102	-1.367	0.116	-11.827
Egress time						
Car	-1.211	0.140	-8.681	-0.792	0.083	-9.571
Public transport	-1.775	0.128	-13.826	-0.947	0.057	-16.680
E-carsharing (main)	-0.760	0.082	-9.287	-1.428	0.067	-21.475
E-bikesharing (main)	-0.387	0.112	-3.451	-1.577	0.149	-10.591
E-scootersharing (main)	-0.616	0.095	-6.499	-1.536	0.117	-13.102
Waiting time						
Public transport	-1.231	0.053	-23.274	-1.152	0.075	-15.365
E-carsharing (main)	-0.150	0.160	-0.939	-1.015	0.159	-6.404
E-bikesharing (main)	-0.945	0.107	-8.796	-0.830	0.119	-6.958
E-scootersharing (main)	-0.296	0.130	-2.282	-1.467	0.148	-9.911
E-bikesharing (access/egress)	-0.677	0.172	-3.943	-0.635	0.187	-3.391
E-scootersharing (access/egress)	0.201	0.077	2.594	-0.243	0.105	-2.305
Walking time						
E-bikesharing (access/egress)	-1.526	0.133	-11.456	-0.903	0.177	-5.101
E-scootersharing (access/egress)	-0.697	0.087	-7.983	-0.991	0.175	-5.661
Walking (access/egress)	0.901	2.064	0.437	-0.260	1.227	-0.212
Travel cost						
Car	0.398	0.064	6.246	-0.331	0.157	-2.109
Public transport	-0.798	0.117	-6.816	1.067	0.094	11.371
E-carsharing (main)	-0.134	0.144	-0.932	-0.708	0.077	-9.205
E-bikesharing (main)	-0.396	0.188	-2.109	-1.482	0.260	-5.707
E-scootersharing (main)	-0.721	0.081	-8.855	0.072	0.115	0.623
E-bikesharing (access/egress)	-0.374	0.068	-5.512	-1.439	0.327	-4.405
E-scootersharing (access/egress)	-0.132	0.078	-1.681	-0.857	0.279	-3.071
Parking cost						
Car	-1.766	0.115	-15.395	-3.438	0.167	-20.584
Availability (%)						
E-carsharing (main)	0.056	0.022	2.574	-0.036	0.017	-2.119
E-bikesharing (main)	-0.195	0.021	-9.267	0.530	0.121	4.392
E-scootersharing (main)	-0.164	0.028	-5.882	-0.013	0.023	-0.586
E-bikesharing (access/egress)	0.040	0.058	0.692	0.104	0.021	4.976
E-scootersharing (access/egress)	0.186	0.045	4.090	0.102	0.013	7.642

LL(0): -9474.02; LL(model): -6046.49; No. of parameters: 114; adj. rho-squared: 0.2322.

Chapter 5

Conclusions

1. Summary

This thesis aimed to establish the critical role of shared electric mobility systems (SEMS) in transforming the urban transportation. SEMS offer a viable alternative to private car usage, addressing issues such as traffic congestion, environmental degradation, rising urbanization, and depletion of valuable land resources. By providing flexible, cost-effective, and environmentally friendly travel alternatives, SEMS hold immense potential for fostering sustainable urban mobility. Nevertheless, their adoption rates remain constrained due to infrastructure inadequacies, limited public awareness, regulatory challenges, and socio-behavioural factors. This thesis tries to emphasize the necessity for targeted interventions to address these barriers and enhance SEMS acceptance across diverse urban communities.

At first, critical barriers and solutions for the widespread adoption of SEMS were identified. By integrating fuzzy logic with best-worst method (BWM) and combined compromise solution (CoCoSo), the study ranks behavioural, policy & governance, infrastructural, technical, and external barriers (and sub-barriers) that hinder the SEMS uptake. Key barriers include the habitual use of private vehicles, lack of visions and coherent policies, perceived costs, uncertain availability and accessibility, and insufficient infrastructure. The study proposed strategic solutions such as developing financial strategies, improving SEMS network and charging infrastructure, implementing financial incentives, optimizing the locations of SEMS stations, and provisions for supportive local authorities in order to increase SEMS usage. It highlights the importance of public-private partnerships and coherent national frameworks to overcome these challenges.

The second study employed a Structural Equation Modelling (SEM) approach to investigate the psychological and behavioural factors influencing SEMS adoption intentions. Integrating the technology acceptance model (TAM) and the theory of planner behaviour (TPB), the study examined variables such as mode-use habit, perceived usefulness, personal innovativeness, social influence, scepticism, and perceived risk in addition to several socio-economic parameters to understand their association with intentions. While the study found significant associations for all latent constructs with expected directions, it is important to note that habit of car-usage has positive impacts user' scepticism and perceived risk, and negative impact on perceived usefulness, underscoring the critical role of habit in shaping adoption behaviours. The study also revealed significant sociodemographic effects, with gender, education, and household characteristics playing moderating roles. This study emphasises the importance of addressing these psychological barriers through targeted policy interventions and user-centric strategies.

The final study explored the adoption of SEMS through a hybrid latent-class latent-variable (LCLV) modelling approach. The study analysed stated preference data collected in England to identify latent user segments based on their habits and sociodemographic characteristics, and to understand behavioural patterns associated with SEMS adoption using alternative-specific service attributes and latent variables (similar to Chapter 3). The results reveal two distinct latent classes with different preferences towards SEMS adoption. It is found that non-habitual individuals, who are also public transport friendly and price sensitive, are more likely to use SEMS. While these individuals are more inclined to micro-mobility options, car users tend to prefer shared e-cars over other SEMS modes. Substitution patterns reveal positive shift from private cars to SEMS modes, and importantly, an unintended shift from public transport to SEMS modes. The study emphasised the need for targeted policies that cater to specific users' segments. It also poses the importance of balanced approach that integrates SEMS into broader urban mobility ecosystem through business-oriented (for operators) and goal-oriented (for sustainability) policies for creating cohesive and efficient yet sustainable urban transport.

2. Policy implications

To fully address the barriers to SEMS adoption and achieve the desired policy goals, a multifaceted approach is essential. Insights from this thesis provide comprehensive recommendations for planner, policymakers and operators to act upon. This section briefly revisits the policy implications discussed throughout the thesis:

1. **Infrastructure investments:** Investing on dedicated infrastructure, such as strategically placed fast charging stations for fast and reliable operations, dense network of SEMS stations, and protected lanes for micro-modes, is pivotal for improving accessibility and user convenience, and ensuring consistent service quality (Roni et al., 2019; Tyrer and Orchard, 2021). This will also help reducing operational inefficiencies and create user-friendly experience, fostering higher adoption rates, particularly for shared e-bikes and e-scooters.
2. **Economic incentives:** Incentives such as subsidies for SEMS services, lower taxes on shared electric vehicles, free trials, and time-sensitive discounts can encourage users to switch from private cars. This may also help users to build new habits of using SEMS modes (Valeri and Cherchi, 2016; Verplanken et al., 1997). Similarly, operators can also benefit from tax relief and grants for fleet electrification and/or station establishment.

In essence, financial measures can lower entry barriers for both users and operators, supporting sustained adoption by making SEMS cost-competitive with private modes.

3. **Regulatory frameworks:** Coordinated and concise policies governing safety, vehicle maintenance, parking restrictions, operational guidelines, and data transparency should be implemented (Zuniga-Garcia et al., 2022a). Such frameworks help build trust among stakeholders and ensure accountability among operators. This is also important to reduce misuse, promotes equitable service distribution, addresses concerns about safety and reliability, and also regulates substitution from public transport modes.
4. **Public awareness campaigns:** Educational initiatives emphasising the environmental, financial, and convenience benefits of SEMS can counteract resistance due to unfamiliarity and/or scepticism. Targeted campaigns, coupled with user testimonials, highlights how SEMS aligns with personal and societal goals (Kaplan et al., 2018; Teixeira et al., 2021). Effectiveness lies in targeting behavioural barriers through these campaigns that can influence cultural acceptance and encourage reliance on SEMS over private cars.
5. **Integration with public transport:** Development of effective connections between SEMS and existing public transit modes through mobility hubs and unified ticketing systems significantly improves multimodal travel and may help complementarity of both transport means over potential substitution (Oeschger et al., 2020). Such integration can reduce dependency on private vehicles by addressing gaps in first/last mile connectivity and enhancing overall system efficiency.
6. **Equity-oriented policies:** Ensuring affordability and accessibility for lower-income and underserved populations is essential for widespread adoption. This includes offering income-based subsidies (or fare pricing) and expanding services to underserved neighbourhood. Equity-based measures democratise access to sustainable transport, increasing transit ridership, and promoting inclusivity in urban and sub-urban mobility systems (Mohiuddin et al., 2023; Wang et al., 2022).
7. **Collaborative governance:** Positive partnerships between public authorities, private operators, and technology providers are of utmost importance for innovation and scalability of emerging mobility. Coherent national frameworks that align municipal goals with operator objectives can encourage mutual benefits. Collaborative models can optimize resource utilization, expand coverage, and ensure that SEMS align with broader sustainable urban mobility goals.
8. **Potential unsustainability of SEMS:** The results showed that SEMS do not only substitute car trips, but also the public transport trips. Although the SEMS hold the potential to replace private car trips, results showed that current car users have weaker preferences for SEMS compared to public transport friendly users. Further, from a life-cycle assessment perspective, SEMS may not always reduce transport emissions when a full environment cost (including manufacturing, relocations for charging and rebalancing demand-supply areas, maintenance and repair works) is considered (Hollingsworth et al., 2019). Hence, it is necessary to understand travel patterns in

application areas, regulate/limit the usage of SEMS/private cars in areas well served by public transport network, and restrict parking supplies in city centres (where generally the most car-commuting occurs) while relocating the same in peripheries of central area to increase the resilience of urban transport.

All in all, these strategies address the barriers and factors influencing SEMS adoption while aligning with the overarching goals of reducing GHG emissions, alleviating traffic congestion, and promoting sustainable urban mobility. However, their effectiveness depends on the local-level implementation, routine evaluations, and stakeholder cooperation to adapt strategies based on user needs and technological advancements.

3. Limitations and future direction

While this research provides valuable insights into SEMS adoption, it is not without limitations that can be reflect upon in future studies. Firstly, a limited geographic scope and demographic context affects the generalizability of the study findings. For instance, the adoption rates in emerging economies or suburb to rural areas may differ significantly. It would be worthwhile to delve into transferability of the implications to regions with different socio-economic, cultural, and infrastructural contexts. For the study in Chapter 2, the opinions from chosen experts might not fully represent the broader stakeholder community. As future directions, this exercise can be done including diverse community perspective that might enhance the robustness of the results. It is important to note that the study in Chapter 4 is relied upon the stated preference data which may come with hypothetical biases, as respondents may not always provide accurate or truthful answers. Additionally, SP data cannot fully capture the real-world behavioural complexities that may lead to unintended consequences. Hence, incorporating spatiotemporal revealed preference data from SEMS usages logs and public transport systems can validate and enhance the current findings. Future research should also explore longitudinal data to capture travel behaviour change over time, including the effects of habit formation or breaking in context of SEMS. The current study is limited to commute trips performed frequently using either private cars or public transport. Similar studies in future can apply the current framework to different trip purposes like shopping, leisure, etc. Besides, the investigation with more comprehensive set of alternatives including personal bikes, mopeds, and ridesharing (e.g., using car as passenger) that might be used for commuting is due in future. This may provide more comprehensive understanding on the realistic potential impacts of SEMS modes, which might be overestimated here.

As a future research direction, this research can be extended to investigate the role of SEMS modes for last mile connectivity in intercity travel. Similarly, it would be interesting to examine the role of shared e-car, if the services would be available for intercity travel (that are generally private car-based). While this and most other studies are focused on user-centric problems, analysing operator-centric challenges, such as fleet management and cost-efficient services, can lead to more robust and sustainable business models. The results of this thesis can be utilised in simulations of real-world scenarios to assess the full lifecycle emissions of SEMS and subsequently quantify their contribution to sustainability goals. Lastly, this study could not examine the association and potential disparity between adoption intentions and actual adoption due to time constraints. Future studies should attend this aspect in order to achieve more realistic results.

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