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Psychological factors impacts on carsharing use

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Abstract

Carsharing services have a significant potential for improving urban mobility by increasing the independence and freedom of travel and reducing traffic externalities. Although car-sharing has been used for over a decade, several aspects need further investigation, such as the impact of user's psychological factors on service use, as well as the factors impacting users' choices between different carsharing operators, in particular their preferences for different payment schemes, and their perceptions of the operators' application rating. Accordingly, four hybrid choice models (HCM) were estimated to investigate factors impacting (i) the knowledge about carsharing services, (ii) carsharing adoption, (iii) the shift from other modes to carsharing, (iv) the choice between carsharing operators with different payment schemes, using a large survey sample (N = 1044 responses 9469 SP observation) from Munich, Germany. The models showed the significance of sociodemographics, such as income level, education level, household size, employment status, ownership of a bike, access to a car, the availability of a driving license, and public transport subscription-based tickets on the carsharing use directly and indirectly, and four psychological factors encompassing different personality traits (i.e., adventurous), travel behavior, and attitudes were found to be significant in the various models; the latter covered service-related attitudes (perceived carsharing app importance) and travel behavior attitudes or profiles (frequent public transport user and frequent shared micromobility user). This research raises questions regarding the inequitable use of carsharing, the impacts of mobile applications on using the service, and the potential of integrating carsharing in mobility as a Service platforms to increase the potential for multimodality.

Keywords Shared mobility · Carsharing · Choice model · Attitudes · Personality

Introduction

In the past ten years, there has been a significant increase in the acceptance, utilization, development, and improvement of app-based shared mobility services. This growth has been made possible by revolutionary advancements in information and communication

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technologies (ICT). Shared mobility services encompass various options, including schemes, services, vehicles, and business models. Examples of these services include ride-sharing and carpooling, in which people share or split a ride, as well as carsharing and shared micromobility options such as bikesharing and e-scooter-sharing, in which vehicles can be rented based on time or distance (Narayanan and Antoniou 2022; Gilibert and Ribas 2019). These new mobility services have changed the landscape of urban mobility by introducing the concepts of on-demand services and pay-per-use, which increases the attractiveness of such services for users due to their ease of use, ease of payment, convenience, but also as they are perceived to be convenient, safe, and environmentally friendly (Arteaga-Sánchez et al. 2020; Tirachini and del Río 2019; Watanabe et al. 2017; Rayle et al. 2016).

Shared mobility services benefits are not limited to the individual level but it could be extended to the city scale and could be an attractive solution for various transportation problems as they do not need large infrastructure investments and are quick to implement in most of the cases (Abouelega et al. 2022). Maintaining, upgrading, and constructing transportation infrastructure generally needs significant investments and a long time to materialize, which is not always a viable solution; one example is extending the transportation system's accessibility to suburban areas with inefficient public transportation's access (Burghard and Dütschke 2019; Abouelega et al. 2022). Shared mobility services could reduce the demand and congestion on roads, as well as the vehicle kilometer traveled (VKT), under the conditions of not replacing public transportation trips and replacing low occupancy vehicles (Tirachini et al. 2020). Alonso-Mora et al. (2017) concluded that shared rides could as well reduce the number of cars on city roads. The same promises of reducing the number of vehicles on the streets could be achieved using carsharing services, as private cars are idly parked for around 90% of the time (Zhang et al. 2015). Transport for London (TfL) sees carsharing services as complementary to public transportation services (Akyelken et al. 2018). Carsharing use could even be correlated with the increase in public transportation use (Aguilera-García et al. 2022).

On the other hand, challenges arise with the introduction of shared mobility should not be overlooked. Several problems have been raised since the introduction, such as increased safety concerns, and the rapid increase of numbers of reported severe and fatal accidents related to shared scooter use (Yang et al. 2020). Other problems related to operational-aspects and governance were also noted, including but not limited to, fleet-size control capping and organization, and permit cost (Gössling 2020). In most of the cases the evaluation of shared mobility impacts on CO₂ emissions did not consider the whole life cycle assessment, and when the whole life cycle was assessed for the cases of shared e-scooter, the results showed that scooters are producing CO₂-equivalent per passenger-kilometer more than the modes they replace (Moreau et al. 2020), in addition to the other negative impacts that could result from shared services, such as attracting commuters from other sustainable modes, and generating extra kilometers traveled (VKT) during redistribution and maintenance processes (Møller and Simlett 2020). Also, the use of shared mobility require access to the Internet, smart-mobile-phone, and digital banking systems, which is not always available for all the population groups, and thus, it creates equitable use problem by being mostly accessible by the high income groups in comparison to the rest of the population (Abouelega et al. 2024).

Overall, the system is attractive to implement as establishing its infrastructure is considered relatively quick, its market is growing and it has the potential to continue growing in the future (Morwinsky 2023; Shaheen and Cohen 2020); however, it is not always an easy process as these services could face several challenges, such as economic viability (Golalikhanian et al. 2021; Poltimäe et al. 2022), in addition to other obstacles, such as use

complexity, limited availability leading to unreliability of the service, responsibility for the usage, long access time, low public awareness, and the required higher population density for economically feasible operation (Nansubuga and Kowalkowski 2021). An example of the struggle is the ShareNow¹ cease of operations in North America and several European cities, such as London, Brussels, and Florence in 2020 (Miljure and Ben 2019). Share-Now attributed ending the service to the rapid changes in the urban mobility landscape, the intense competition with different providers of different services, the unavailability of adequate infrastructure (e.g., charging infrastructure for electric vehicles), and the increased operation cost raising concerns regarding the long term economic model feasibility (Pyzyk 2019; Miljure and Ben 2019). On the other hand, there is a recent increase in the service's popularity and adoption in Western European cities and Russia. This increase is conditional based on the city's characteristics, such as the population's educational level, university presence, and the number of Green party voters (Kireeva et al. 2021; Münzel et al. 2020). Therefore, it is essential to note that the implementation of the service and its economic viability is not always granted, and careful consideration, especially in the planning phase, should be attained.

Carsharing is a form of shared mobility that provides easy access to on-demand car use without the burden of car ownership responsibilities, the need to process paperwork such as for car rental services, or even the need to return the vehicle to the pickup points in most of the cases (Liao and Correia 2022). Carsharing services operate on different schemes when it comes to pickup and drop-off arrangements, with three main schemes: round-trip systems, where users pick up and return vehicles to the same locations, and more flexible options like one-way trips or free-floating systems, where vehicles can be dropped off at any designated point within a specified area (Amirnazmiafshar and Diana 2022; Jorge and Correia 2013).

Carsharing services and other shared mobility services are not only changing the landscape of urban mobility, but also the traditional idea of a car manufacturer producing, buying, and selling vehicles. Currently, some leading car manufacturers are promoting themselves as mobility providers (Akyelken et al. 2018), including Mercedes-Benz Group, BMW, Volkswagen, Toyota, and General Motors. Mercedes-Benz Group has two carsharing services (ShareNow, and Croove), acquired two taxi services (myTaxi,² and Hailo), is investing in two ride-hailing services (Via,³ and Blacklane⁴), and starting its own mobility platform moovel⁵ (Akyelken et al. 2018). Therefore, there is an essential need to understand in-depth the different aspects of these services for better operation and integration within the urban environment.

Some of the main aspects of shared mobility that are important for the different stakeholders are the socio-demographic characteristics of the users and their general travel behavior, as well as their impacts in deriving the demand and identifying user target groups (Jochem et al. 2020). Psychological factors such as attitudes, perceptions, and personality traits play a significant role in individual travel behavior and mode choices (Kroesen and Chorus 2020). The importance of understanding the impact of psychological factors on

¹ ShareNow is a merger company between Car2Go the carsharing subsidiary of BMW, and the DriveNow, the subsidiary of Mercedes-Benz Group (<https://share-now.com>).

² <https://free-now.com>, now the service is a joint venture between Mercedes-Benz Group and BMW.

³ <https://info.ridewithvia.com>.

⁴ <https://blacklane.com>.

⁵ <https://moovelus.com>, the platform is one of the Mobility as a Service (MaaS) providers.

travel behavior and mode choice lies in their ability to facilitate encouraging the use of the modes of interest, as they could be described as the underlying motivation for specific mode use (Bhagat-Conway et al. 2024). Previous research has shown that attitudes were found to have a significantly higher impact on the use of shared mobility as compared to sociodemographics, such as in the case of pooled rides (Abouelela et al. 2022). Still, there is a gap in terms of existing research on attitudes and personality traits in the scope of carsharing and shared mobility in general, mostly when comparing it to studies focusing on sociodemographics, which have been well examined and explored in the literature (Monteiro et al. 2023; Efthymiou and Antoniou 2016; Efthymiou et al. 2013). Several of these psychological factors are still under exploration and their role in the mode choice travel decision (Rahimi et al. 2020a) in general, and shared mobility use in particular, is not well understood. To the best of the authors' knowledge, many aspects of carsharing services have not yet been studied, such as the perceived service and feature offerings by different carsharing operators, including digital operator aspects (often reflected in the operator rating on the app store), as well as their impact on service adoption and use frequency (Monteiro et al. 2022).

The digital dimension of the carsharing services has also not been investigated in-depth, and includes the mobile application friendliness and ease of use, the service provider's website landing page, the digital marketing of the service, the online marketing campaigns, and the business-to-business offers (Janasz and Schneidewind 2017). Another service feature to consider is the operator payment schemes (per minute or kilometer as recently introduced by some operators). The impact of the above-mentioned features on the operator choice still needs to be investigated. Finally, carsharing research on adoption and use has not yet been totally understood due to the novelty of the services; a large number of the carsharing studies have been completed before the services were even launched or during the early operational and adoption stages, during which users might have a different use behavior as they are getting familiar with the service. Another motivation of this paper is therefore to contribute to the existing body of research with more timely study in which the operation of carsharing services is ongoing at the time the research is done (Le Vine and Polak 2019; Hjorteset and Böcker 2020).

We therefore contribute to the current literature by updating the knowledge regarding carsharing use, using user-level information through a large online survey, and answering the following two research questions (RQ) investigating the roles of users' psychological factors: personal attitudes, travel behaviour, and carsharing-related features on the different aspects of carsharing services.

- RQ1) How do users' psychological factors impact carsharing adoption and use?
- RQ2) What factors impact the choice between different carsharing operators?

The rest of the article is organized as follows; “[Literature review](#)” section summarizes some of the selected studies related to user factors and attitudes impacting carsharing use and the different service-related characteristics that impact user's choices. In “[Methods and study set-up](#)” section explains the methods used in the research and the case study setup used for the analysis and modeling. In “[Analysis results](#)” section spans across two parts that answer the research questions (RQ1 and RQ2); first, we analyze the collected data, second, we model the different factors that impact carsharing adoption and use, with a special focus on personality traits and attitudes. We also model and extract the factors impacting users' choices between different carsharing operators. Finally, “[Discussion, limitations, and conclusions](#)” section discusses the study findings, highlights the policy implications, and summarizes the conclusion.

Literature review

The benefits of carsharing

Sustainability is one of the many benefits associated with carsharing; it is considered a sustainable mode of transportation that has a wide array of positive impacts on the urban environment, such as the reduction in household car ownership and, subsequently a reduction in Greenhouse Gas (GHG) emissions that could reach up to 30–54% as a consequence of reduced Vehicle Miles/Kilometers Travelled (VMT/VKT) (Shaheen et al. 2019; Nijland and van Meerkerk 2017; Martin and Shaheen 2011a). Also, electrification of the carsharing fleet was proven to be environmentally advantageous (Luna et al. 2020) and was able to yield more than 30% reduction on carsharing users' GHG even if there was no change in VKT (Namazu and Dowlatabadi 2015). Several examples of the previous positive potentials of carsharing use were observed; in Germany, evidence associated with the reduction of car ownership and the number of station-based carsharing in the same area were present (Kolleck 2021); in China, in 2017, carsharing has caused a significant reduction of energy used, and CO_2 emissions, with the expectation of higher savings by 2025 (Te and Lianghua 2020).

Shaheen et al. (2019) and Martin and Shaheen (2016) observed a decline in the average VKT of carsharing users ranging from 6 to 63% in North America, considering several conditions such as giving up car ownership, and the type of the service one-way or round trip. These tendencies were further corroborated by studies in Palermo, Italy (Migliore et al. 2020), the Netherlands (Nijland and van Meerkerk 2017), and London, UK (Wu et al. 2020). Also, Wu et al. (2020) noted that in London, higher satisfaction with the proximity to carsharing vehicles contributed to a larger reduction in VKT. Interestingly, carsharing users who live in suburban areas tend to drive fewer kilometers than their counterparts in dense urban areas (Clewlow 2016), which could be attributed to the lower density of available vehicles in the suburbs, resulting in carsharing users canceling the non-essential trips. Other environmental-related positive impacts, such as saving materials and reducing wastes, were observed (Harris et al. 2021). The environmental impacts of carsharing and their total magnitudes are heavily dependent on the occupancy rate, the used vehicle and fuel type of the fleet, the modal share of carsharing, the modes replaced by carsharing, and the vehicle's lifespan (Poltimäe et al. 2022; Harris et al. 2021; Jung and Koo 2018). Also, adverse environmental impacts of carsharing were observed; in Palermo, Italy, the fleet only contains diesel and natural gas vehicles, and it was found to increase the CH_4 and NO_x emissions of the city (Migliore et al. 2020).

Impacts related to infrastructure and built-environment were also observed, as carsharing use can help in reducing car ownership rates, which promotes more positive impacts on curb-side management, minimizing the space uptake for car parking (Golalikhani et al. 2021). A study among students in Ithaca, New York by Stasko et al. (2013) found that since the introduction of carsharing in the area, student parking permit sales had declined despite a continuous increase in enrollment. The causality of these occurrences was not investigated or verified. Another survey in France investigated carsharing use impact on parking derived that for every carsharing vehicle on the street, between 1.6 and 4.2 on-street parking spaces, 0.3–0.6 public parking spaces, and 2.1–4.2 private parking spaces could be eliminated (6t-Bureau de recherche and ADEME 2016). Diana and Chicco (2022) analyzed the spatial distribution of changes in parking demand related to carsharing and

found that more relieved parking spaces could be anticipated for central areas, while more negative impacts might be imposed on the parking in peripheral areas.

Integrating carsharing with public transportation would yield more benefits by extending the spatiotemporal accessibility of public transportation. Some examples of this integration are the decentralized mobility hub (Czarnetzki and Siek 2022), implementation of dedicated carsharing facilities (Engel-Yan and Passmore 2013) and unbundled parking (Schure et al. 2012) in residential buildings, and appropriate financial and policy backing from the authorities in forms of aids to the low income-groups (Rabbitt and Ghosh 2013; Bocken et al. 2020). Note that the extent of carsharing impacts could highly vary depending on the region, built environment (Clewlow 2016; Jain et al. 2022), accessibility of public transportation, and the carsharing replaced modes (Shaheen et al. 2019; Jain et al. 2022; Kolleck 2021; Duncan 2011). Other positive potentials for carsharing use were observed, but they were less explored, such as benefits associated with the B2B carsharing model capabilities of reducing work trip cost as the car can be used without bearing ownership-related costs and duties, increasing thereby not only trip sustainability, but also the workplace attractiveness, which could now subsidize carsharing trips for their employees (von Wieding et al. 2022). Carsharing trips were also found to encourage multimodality, physical activities, and a healthier lifestyle (Kent 2014; Shaheen et al. 2019; Harris et al. 2021). Also, carsharing was found to increase access to cars for car-less households (who do not own private vehicles), providing them thereby with more independence and equitable access to opportunities (Stasko et al. 2013; Kent 2014; Shaheen et al. 2019). This in turn improves the mobility of lower-income groups by increasing the number of available travel options (Kumar Mitra 2021), and strengthening the sense of community among users (Hartl and Hofmann 2022; Harris et al. 2021).

Factors impacting the adoption and use of carsharing

Several factors impact the adoption and use of carsharing services; these factors could be categorized into three main groups; (i) service-related factors, (ii) exogenous factors, and (iii) user-related factors. The first group of factors included the number of available vehicles in the stations, and vehicle age; in a study by De Lorimier and El-Geneidy (2013), this encouraged carsharing use in Quebec, Canada. In metropolitan Vancouver, lowering the membership fees was found to attract more users (Namazu et al. 2018). The difference between the trip cost, and the mode carsharing replaced was found to be the most significant factor impacting carsharing use in Beijing, China (Yoon et al. 2017). Personalized use incentives were also found to attract more users (Feng et al. 2023). In Shanghai city, electrical vehicle battery charging level and the number of available vehicles in stations impact the user choice for the vehicles (Hu et al. 2018b). Secondly, exogenous factors are also key such as adverse weather conditions (Yoon et al. 2017), availability, accessibility of public transportation station (Balac et al. 2015; Hu et al. 2018a; Khan and Machemehl 2017), land-use (Kim et al. 2012; Stillwater et al. 2009), intersection and road density, and the availability of parking (Chen et al. 2018; Yoon et al. 2017; Hu et al. 2018a).

Thirdly, several studies focused on investigating the sociodemographic characteristics influencing carsharing use. The findings of these studies have identified users as young, male, well-educated, with high-income, and full-time employment (Le Vine and Polak 2019; Martin and Shaheen 2011a; Alemi et al. 2018; Ahmed et al. 2021; Luo et al.

2019). The role of other important personal drivers to the service is less known, and here we mean the personal attitudes and personality traits, despite the fact that there is evidence suggesting the significance of attitudes on the use and adoption of carsharing services, noting that understanding personal attitudes is claimed to enhance the models predictability (Pronello and Gaborieau 2018). For instance, carsharing users are more likely to own “greener” vehicles (Clewlow 2016) and exhibit more eco-friendly behavior (Jung and Koo 2018), hinting at higher concerns towards environmental issues, and carsharing advocacy attitude increased the adoption of carsharing compared to other modes (Li and Kamargianni 2020). In the realm of carsharing, research on the role of personal attitudes has yielded mixed conclusions.

Zhang and Li (2020) and Li and Zhang (2021) discovered that subjective/social norms had the biggest influence on the intention to use carsharing, and attitudinal variables, including environmental concerns, imposed a much more limited impact, while a study in Taiwan (Buschmann et al. 2020) reported the complete opposite. Varieties also exist within the range of behavioral constructs that were found to be significant in carsharing familiarity and adoption. Aguilera-García et al. (2022) found that high sharing propensity, variety-seeking lifestyle, and preference for driving positively impacted familiarity, and that pro-environmental behaviors reduced carsharing usage. On the other hand, Thurner et al. (2022) concluded that people who were believers of science and technology, who were generally early adopters of novel technology, and those with self-expressive social values tended to be carsharing adopters. The previous discrepancies are unsurprising, considering the virtually unlimited spectrum of attitudes that humans might have. Yet, researchers are constrained to investigate only a select few, along with behavioral indicators which vary across the board.

Cultural context also moderates the effects of other sociodemographic variables. For instance, society could be more concerned about conforming to the norms than their expressions, leading to subjective norms being more influential in their decisions. Also, there is a complex interrelation between these attitudinal constructs, which is hard to interpret. This is well demonstrated by Zhang and Li (2020), Burghard and Scherrer (2022), Li and Zhang (2021), Acheampong and Siiba (2020) in which environmental attitudes imposed no direct impact or even negative impact on carsharing intentions, while simultaneously being positively correlated with another construct which in turn positively impacted the carsharing intention (i.e., positive indirect impact). This shows how the role of attitudes in human decision is a complex topic and requires further research with a possibly wider range of attitude constructs. For example, Hjortset and Böcker (2020) further differentiated the resulting attitude towards carsharing into general interest, anticipated intention, and actual decision to utilize the service. Another part of human attitudes is personality traits, which are the main drivers of travel demand (Mokhtarian et al. 2001). Different personality traits are hypothesized to impact travel behavior differently; while the adventure-seeker personality was found to be likely to travel and drive faster than other personalities, are prone to have and create more elements of danger (Furnham and Saïpe 1993). Redmond (2000) concluded that people with adventure-seeking personalities are more likely to enjoy leisure trips over work trips and may also prioritize them. Another personality associated with the preference for using private cars over public transport is the organizer personality (Redmond 2000). A summary of the factors impacting carsharing use is presented in Fig. 1 below.

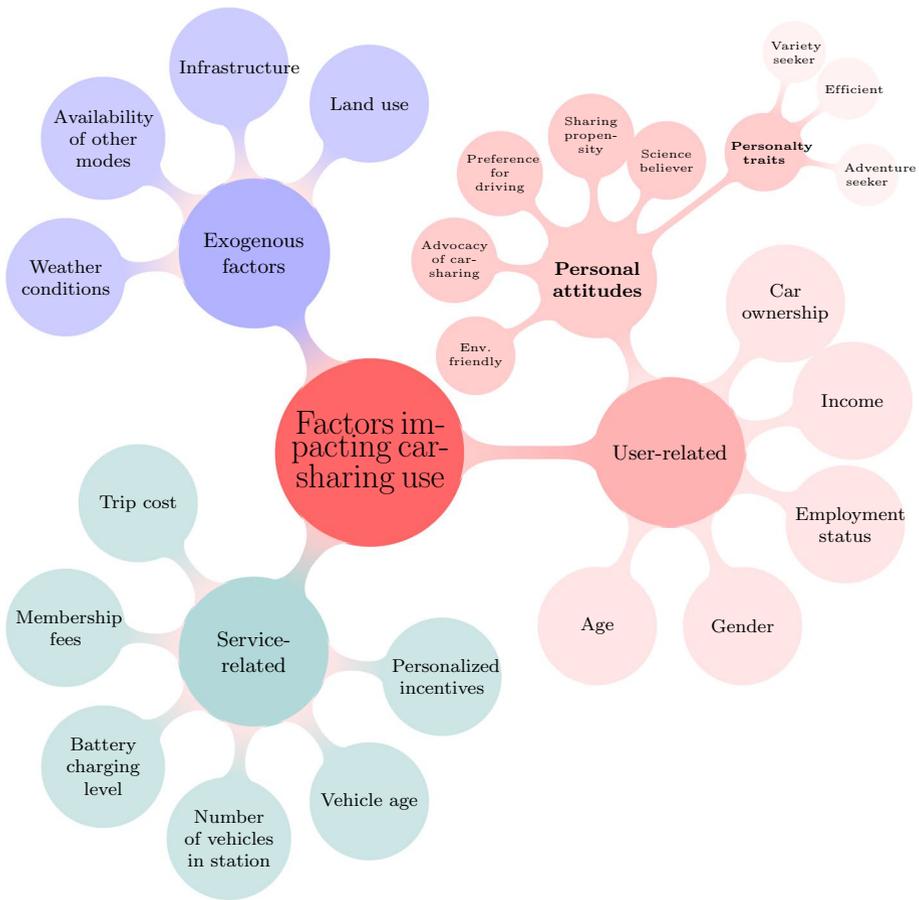


Fig. 1 Summary of factors impacting carsharing adoption and use (*own illustration*)

Synergies between carsharing use and travel behavior

Carsharing might play a significant impact on travel behavior and users' long and short-term travel decisions. It can impact the decision to give-up a car and forego/delay the decision to acquire a new one (Ko et al. 2019; Seo and Lee 2021). Although varying conclusions exist across case studies, the general consensus suggests a decline in the level of car ownership, with studies quoting four (Migliore et al. 2020; Shaheen et al. 2018) to twenty-three (Lane 2005) private vehicles being replaced for every carsharing vehicle in operation. This conclusion is consistent with Le Vine and Polak (2019) findings, which highlighted, based on a survey in London (N = 347 responses), that as much as 37% of respondents had their car ownership decisions impacted by using carsharing, as users opted to drop the decision of buying a car or dispose of their currently owned car. Factors affecting a user to dispose or forego buying a car include income level, age, housing type, satisfaction towards the carsharing service, access time to carsharing station, fuel type, and the price or cost of the service (Jung and Koo 2018; Ko et al. 2019). Simultaneity bias can also be a concern as Jain et al. (2020) found within their case study; carsharing mostly acted as an enabler of

mobility lifestyle change but was not the primary cause of households shedding their private cars, as life events had a stronger influence.

Furthermore, carsharing's overall impact on sustainability depends on the modes it replaces, whether they are "greener" and more active modes such as walking, cycling, and public transportation (Chicco and Diana 2021). The impact of carsharing on the general car use is less conclusive as some studies reported that the majority of carsharing users drove less frequently (than before carsharing adoption) (Martin and Shaheen 2011b; Shaheen et al. 2018), while others studies claimed the contrary (Stasko et al. 2013; Martin and Shaheen 2016). This is due to the fact that the effect of those who dispose of private cars is counterbalanced by the impact of those who gain access to cars through carsharing (Lane 2005). While such studies often relied on user surveys, the latter have often been criticized as they focus on carsharing users and therefore create self-selection biases, which might impact the conclusions.

Modeling techniques

Attitudes are often treated as latent variables derived from stated behavioral statements. To capture these latent attitudes and determine the indicating constructs, several methods have been used in the past, including Structural Equation Models (SEMs) (Yazdanpanah and Hosseini 2016; Aguilera-García et al. 2022; Rahimi et al. 2020b; Zhang and Li 2020), Principal Component Analysis (PCA) (Queiroz et al. 2020; Thurner et al. 2022), and Latent Class Analysis (LCA) (Olaru et al. 2021). Subsequent regression analysis [e.g., Bivariate Logit (Queiroz et al. 2020), and Hybrid Choice Model (HCM), or Integrated Choice and Latent Variable models (ICLV) (Sun et al. 2021)] incorporating the latent attitudinal variables in models is frequently conducted to assess the causality between attitudes and other variables in question (e.g., acceptance of carsharing). The main objective of this integration is to enhance the model's ability to understand the choice process by incorporating the user's cognitive behavior, attitude, and psychological factors into the choice model. This integration also aims to improve the model's goodness of fit where applicable (Vij and Walker 2016; Temme et al. 2007; Ben-Akiva et al. 1999). ICLV models were, for instance, used to quantify the factors impacting the frequency of pooled-rides uses in Mexico City, Mexico (Aboueila et al. 2022). Theory of Planned Behavior (Jain et al. 2021; Zhang and Li 2020; Li and Zhang 2021), Rogers et al. (2014)'s Theory of Innovation Diffusion (Jain et al. 2021; Burghard and Scherrer 2022), and the Theory of Reasoned Action (TRA) along with its extensions (Buschmann et al. 2020) are often incorporated in assessing the role of personal attitudes. Further scientific frameworks that are prevalent in this research topic are the Technology Acceptance Model (TAM) (Al Haddad et al. 2020; Schlüter and Weyer 2019; Buschmann et al. 2020) and its modifications, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Fleury et al. 2017).

Gap analysis

The review of the current research shows several gaps in the current body of literature that need to be bridged to utilize the maximum benefits of shared mobility use, specifically carsharing services. First of all, a significant portion of carsharing-related studies were developed before the implementation of the services or during the early deployment stages. Accordingly, there is a pressing need to update the current literature with more recent studies, especially for users who are already familiar with the service and have used

it for an extended period (Hjortset and Böcker 2020; Le Vine and Polak 2019; Namazu et al. 2018). The importance of covering this point is to test the previously anticipated or observed pre-and-early-use behavior of carsharing and decide if the current operations and policies might need modification or changes.

Secondly, the investigating of the impact of carsharing-related features, such as operator offering and the used mobile app, on service use, adoption, and choice between different operators is still scarce in the existing body of the literature and generally overlooked (Monteiro et al. 2022). As discussed in the following sections, such aspects significantly impact service adoption and use.

Finally, the impacts of psychological factors such as personal attitudes and personality traits on the use and adoption of carsharing services are not well established (Aguilera-García et al. 2022), despite their essential impacts on travel behavior and mode choice, and the use of the different shared mobility options (Abouelela et al. 2022). Understanding the interaction between the different psychological factors and travel behavior is essential to understanding how they could alter the current travel behavior to be more sustainable (Steg 2007). In other words, shared mobility, especially carsharing services, a niche service, and understanding these psychological factors impacting their use could help in driving policies that increase the sustainable adoption of these services (Burghard and Scherrer 2022), for example, social norms were found to be positively increasing the adoption of carsharing when it was promoted as a low-carbon mobility option in Sweden (Mundaca et al. 2022b, a). Also, the role of psychological factors is not only limited to understanding and altering travel behavior, but it also could help in anticipating which policies, such as environmental policies, could be accepted (Ejelöv and Nilsson 2020). Therefore, we are trying to understand additional psychological factors that might impact carsharing use, to understand how to integrate the service with other modes of transport, and which factors could attract users to the service or be used as a pull measure.

In summary, this study addresses the gaps mentioned above by testing the impacts of different psychological factors, namely personality traits, regular travel behavior, and attitudes (importance of service-related features), on carsharing use and adoption, thereby answering the research questions.

Methods and study set-up

Methods

Survey design

The main goal of this research is to understand the impacts of attitudes, travel behavior, and personality traits on the use of carsharing services; therefore, we designed a survey in four parts, which was implemented online using Limesurvey platform (<https://Limesurvey.com>), and disseminated to different users group in Munich, Germany, during the period of 20 of January to 25 of March 2022. We opted to deploy the survey online as it was deployed during the COVID-19 pandemic, and we wanted to eliminate the chances of infection during the data collection process. As carsharing users are likely young, we targeted them in our data collection process. Young users are commonly adopters of shared mobility in general and carsharing in particular, as highlighted in studies in different locations, such as in Munich and Madrid (Aguilera-García et al. 2022), in

Vancouver, Canada (Namazu et al. 2018), in Puget Sound region in the state of Washington, USA (Dias et al. 2017), and all over Germany (Burghard and Dütschke 2019). Also, we collected data from non-users to check the different reasons for not adopting the service, as well as to evaluate the differences between the two groups. Overall, we collected 1170 completed responses, and the average survey completion time was 12 min. The survey consisted of four main parts;

- In the first part, general travel behavior was investigated, where users were asked to specify their usage frequency for different urban modes of transport, whether they had a public transportation subscription ticket (such as a monthly ticket), whether they owned bikes, e-bikes, a private car, and whether or not they had a valid driver's license in Germany. The modes that their use frequency was investigated are:

1. Bus	5. Personal bike	9. Taxi
2. Car as a passenger	6. Shared bike/E-bike	10. Train
3. Car as a driver	7. Shared E-scooter	11. Underground metro
4. E-hailing	8. Suburban train	12. Walking

- In the second part, we investigated user familiarity with and usage of carsharing services; we focused on usage frequency, willingness to walk to the vehicle pickup location, trip purpose. Respondents were also asked about the modes they would have used instead of carsharing for their last carsharing trip. Finally, respondents were asked to evaluate the importance of different aspects of carsharing services, such as mobile-application rating on the digital store, application ease of use, service availability in different cities, service availability in EV, service availability in the airport, service availability in different size vehicles (SUV, trucks, etc.), and the availability of offers bundles (discounts, e.g., for all-day rental, and long-distance rentals).
- The third part of the survey was the stated preference experiment; refer to Fig. 2. In this experiment, respondents had to choose one carsharing service to perform an 11-kilometer trip; the choice was between operator A, where the user pays a fixed cost per kilometer. The other choice was operator B, where the trip cost would vary between a minimum cost, an average cost, and a maximum cost based on congestion conditions. The latter (cost range) would vary based on speeds (maximum, average, and minimum, respectively) of previous trips (previous trip distribution).

Table 1 shows the attributes and their corresponding levels that were used for the experiment. We opted to use travel cost, as it is a decisive factor in travel mode choice, and we wanted to investigate two new factors that were not investigated previously, which are the access distance users needed to walk to the nearest available vehicle and the service rating on the digital application store. The attribute levels were calculated as follows:

Travel cost:

* **Operator A**, payment by km scheme, the average cost per km is 0.89 €/km, obtained from the operator's online website and is similar to values used by Abouelela et al. (2021). A variation of this level (-0.25% , 0% , $+25\%$) would result in a range of (0.66, 0.89, and 1.11) €/km.

Carsharing services are gaining popularity for their ease of use, and their increased availability in our cities, especially among the young population. The service was initially priced by the minute of use, but now there are new schemes of paying a fixed price per kilometer. The main difference between the two schemes is the certainty regarding travel time, as users might encounter delays that would increase the trip cost if users are paying per minute of use and not by kilometer traveled. In the following scenarios, we ask you to choose the most convenient option to use based on your evaluation of the available options based on a hypothetical 11 km long leisure trip in Munich, Germany noting the following:

- **Travel cost**: fixed if you choose to pay per kilometer and could fluctuate if you pay per minute based on the unknown road conditions and unexpected delays.
 - **Min cost**: The minimum expected cost based on fastest speed of previous trips
 - **Avg cost**: The average expected cost based on the average speed of previous trips
 - **Max cost**: the maximum expected cost based on the slowest speed of previous trips
- **Access distance in meters**: the distance you will need to walk to pick up the carsharing vehicle
- **Application rating in store**: the used operator app users' rating on the digital store you use

	Operator A Payment by KM Fixed cost	Operator B Payment by Minute
		cost depends on congestion conditions
Travel cost in €	7.34 €	Min 5.6 €
		Avg 8.1 €
		Max 12.1 €
Access distance in meter	150 m	150 m
Application rating on digital stores (stars)	4 Stars	3 Stars
Engine type: Electric	Yes	No

Certainly A	Probably A	Indifferent	Certainly B	Probably B	None
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Fig. 2 Scenario details and one block example

Table 1 Stated preference attributes and levels

Variable (unit)	Levels	
	Operator A (payment by km)	Operator B (payment by minutes)
Travel cost €	[7.3, 9.8, 12.2]	Minimum cost [5.6, 7.1, 9.2] Average cost [8.1, 10.3, 13.2] Maximum cost [12.1, 15.4, 19.8]
Access distance (m)	[50, 100, 150]	[50, 100, 150]
Application rating (★)	[3, 4, 5]	[3, 4, 5]
Engine type: electric	Yes/No	Yes/No

* **Operator B**, based on actual carsharing speed distribution. Essentially, minimum, average, and maximum costs were calculated using the same carsharing trips in Munich, Germany, for 2016, as described in Abouelela et al. (2021). The trip cost was calculated based on the speed distribution and multiplied by the cost per minute. The minimum cost was calculated based on the average speed for the first speed quartile distribution. The average speed was calculated based on the average speed, and the maximum cost was calculated based on the third-speed quartile average speed. For each speed, subsequent cost (- 0.25%, 0%, +25%) values were calculated.

* **Operator B**, costs per minute were obtained from operators' online websites and similar to the values used by Abouelela et al. (2021).

- The levels of access distance calculated for this experience considered that the walking speeds are around 4–6 km/h (Bohannon and Andrews 2011), and that more than 50% of pooled ride users opted to walk less than ten minutes for the ride pick up location (Abouelela et al. 2022).
- Application rating on the digital application store was created specifically for this experiment, as no similar attributes were not investigated before.
- Engine type was used to check the impact of the electric engine type on the user's choice, and it was a binary attribute with two levels: yes, and no. A similar attribute was used by Monteiro et al. (2022).

The fourth part of the survey investigated the sociodemographic characteristics of the users, where we asked users to specify their age, gender, education level, occupation, number of people and children in the household, and average monthly income. Also, in this part, we asked users to specify their agreement on a five-points-scale (totally disagree, disagree, neutral, agree, totally agree) on how much they identify with each of the 18 personality traits below, as used by Queiroz et al. (2020), Mokhtarian et al. (2001), Redmond (2000):

1. Optimist	7. Like to stay close to home	13. Creative
2. Adventurous	8. Efficient	14. Calm
3. Like routines	9. Variety seeking	15. Anxious
4. Spontaneous	10. Punctual	16. Like being in charge
5. Like being outdoor	11. Like to be alone	17. Participating
6. Risk taker	12. Independent	18. Lazy

Modeling framework

The main target of this research is to model the impact of attitudes and personality traits on carsharing use, using the collected survey data. The survey consists of answers to attitudinal and personality evaluation, revealed preference, and stated preference questions. The different parts of the survey were used to answer the research question related to investigating factors impacting adoption, the shift from other modes, the choice between operators, and finally, the knowledge or awareness level regarding carsharing service (essentially the research questions RQ1 and RQ2). In investigating the examined factors, Hybrid Choice Models (HCM) were estimated. The main purpose of estimating HCM models was to integrate and investigate the impacts of user cognitive behavior, personality, and attitudes on the service adoption (Abouelela et al. 2022; Bolduc and Alvarez-Daziano 2010; Ben-Akiva et al. 2002), but also to get a more realistic choice behavior, as pointed out in Raveau et al. (2010), Bolduc and Alvarez-Daziano (2010).

The first step in HCM is to estimate the latent constructs of the data (namely attitudes, travel behavior, and personality) using Exploratory Factor Analysis (EFA). We started the analysis by performing a scree test (Cattell 1966) to decide on the optimum number of factors. The test showed two factors as the desired number, and we kept attributes with factor

loading 0.4 or larger, based on the sample size and following (Hair et al. 1998). Varimax rotation was applied to obtain an orthogonal structure between the different factors, and the polychoric correlation was used as it suits the ordered nature of the data better than other correlation methods (Holgado-Tello et al. 2010). After deciding on the estimated factors for each of the question groups, the corresponding discrete outcome model was first estimated, and the latent variable model was added afterward. Four HCM models were estimated using Apollo package (Hess and Palma 2019) under the statistical software R (R Core Team 2023).

Study setup

Munich is the third largest city in Germany, with a population of around one and a half million and six million inhabitants in the metropolitan area (Aguilera-García et al. 2022). The city has a strong transportation infrastructure network reflected in many aspects of the inhabitants' daily travel behavior, where 80% of the population owns at least one bike, served by a 1,200 km long bike lanes network and 28,000 bike parking spaces. Also, the overall city modal shift reflects the solid public transportation culture, where 33% of the trips are made by cars, 23% by public transportation, and 44% of daily trips are done by active mobility, walking and biking.⁶ The city-shared mobility landscape is vibrant, with different options for carsharing, bikesharing, shared e-scooters, moped scooters, and e-hailing. Munich City demonstrates an excellent example of a case study for carsharing use city, with the free-floating carsharing service starting in 2011. In 2019, there were around 2100 shared cars on the city streets. Different operators adopt different pricing schemes, such as pay per minute, hour, and day, and lately, some operators are calculating trip prices based on trip length (Aguilera-García et al. 2022).

Analysis results

Summary of sociodemographic and travel behavior characteristics

The survey resulted in 1170 valid and complete responses. Table 2 shows the collected sample demographic characteristics compared to the city of Munich. The collected data is skewed compared to the city population in terms of age, education, occupation, and income, which is a direct result of the sampling strategy targeting young users. In general, the sociodemographic characteristics of the shared mobility users are different from the ones of the average population, as discussed in “Literature review” section.

In terms of age, 89% of the sample is younger than 36 years old, compared to 40% of the average city residents age; also, users are highly educated, with 85% of the sample having at least a bachelor's degree compared to 26% of the city's residents. The number of students in the sample is over-representative in comparison to the city, as 43% of the sample respondents are students compared to only 4.5% of the city population. Therefore, the age and occupation of the respondents are reflected in other aspects, such as income being lower than the city average and the low number of children in the households. As the focus target group of this research are users younger than 35 years old, we only considered

⁶ <https://civitaS.E.u/cities/munich>, last accessed 30/05/2023.

Table 2 Summary of sample demographics and travel behavior and comparison with the Munich Census (2011)

Variable	Subgroup	n (pct%)	User	Non-user	Munich census	
Age	18–24	415 (35%)	175 (30%)	240 (40%)	(18–29) 27.2%	
	25–30	521 (44%)	272 (47%)	249 (42%)		
	31–35	108 (9.2%)	68 (12%)	40 (7%)	(30–39) 16.7%	
	36–40	46 (3.9%)	29 (5%)	17 (3%)		
	41+	81 (6.9%)	34 (6%)	47 (8%)	(40+) 51.5%	
Gender	Female	523 (45%)	241 (42%)	282 (48%)	51.70%	
	Male	648 (55%)	337 (58%)	311 (52%)	48.30%	
Education level	Masters & PhD	386 (33%)	219 (38%)	167 (28%)	(PhD 2.5%)	
	Bachelor	657 (56%)	309 (53%)	348 (59%)	Bachelor/MS: 22.7%	
	High school or less	128 (11%)	50 (9%)	78 (13%)	66.90%	
Monthly income	500€ or Less	140 (12%)	40 (6.9%)	100 (17%)	Avg: 4220 AC/ household	
	500€–2000€	580 (50%)	259 (45%)	321 (54%)		
	2000€–4000€	259 (22%)	159 (28%)	100 (17%)		
	4000€ and more	192 (16%)	120 (21%)	72 (12%)		
Occupation	Full time	405 (34.6%)	258 (45%)	147 (25%)	Full/part-time 87.1%	
	Part-time	165 (14.1%)	81 (14%)	84 (14%)		
	Self employed	43 (3.7%)	14 (2.4%)	29 (4.9%)		
	Student	510 (43.6%)	208 (36%)	302 (51%)		4.50%
	Other	48 (4.0%)	17 (3%)	31 (5%)		8.40%
Children	No	1,019 (87%)	491 (85%)	528 (89%)		
	Yes	152 (13%)	87 (15%)	65 (11%)		
Household size	1	441 (38%)	200 (35%)	241 (41%)	50.30%	
	2	296 (25%)	174 (30%)	122 (21%)	28.80%	
	3 and more	434 (37%)	204 (35%)	230 (38%)	20.90%	
PT ticket*	Yes	859 (73%)	407 (70%)	452 (76%)		
	No	311 (27%)	171 (30%)	141 (24%)		
Own bike or E-bike	Yes	595 (51%)	335 (58%)	260 (44%)		
	No	575 (49%)	243 (42%)	333 (56%)		
Car access	Yes	451 (39%)	243 (42%)	208 (35%)	44%	
	No	719 (61%)	335 (58%)	385 (65%)	56%	
Driving license**	Yes	523 (45%)	343 (59%)	180 (30%)	88.90%	
	No	647 (55%)	235 (41%)	413 (70%)	11.10%	
$N_{Total} = 1170$			$N_{User} = 578$	$N_{Non-User} = 593$		

*Subscription-based tickets; **Valid in Germany

them in the following analysis, excluding all the other users (N = 1044). When comparing carsharing users with non-users, using a Pearson’s Chi-square test (χ^2) (Pearson 1900), the differences were found to be significant in terms of users being males, more educated, with higher income, compared to the average population, full-time occupation, having access to a car, and owning a driving license that is valid in Germany. This profile of the carsharing user is similar to other shared mobility services in other locations, such as the United

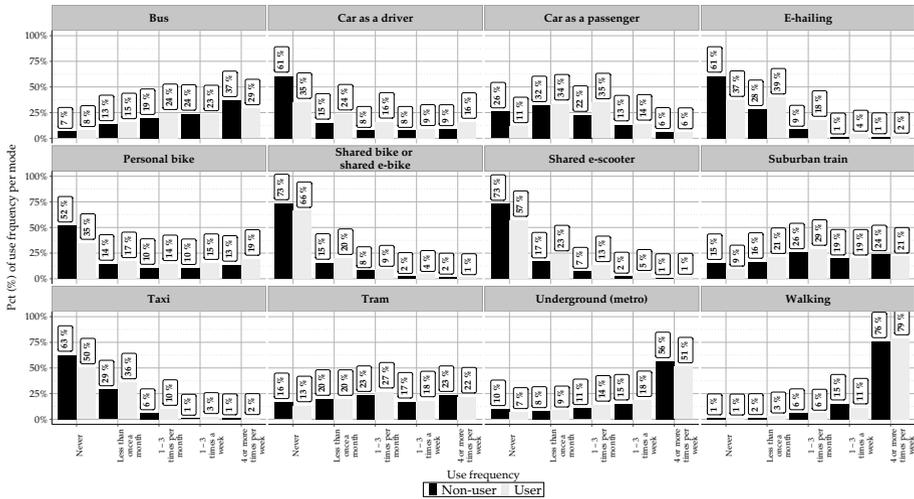


Fig. 3 Urban modes use frequency for users and non-users of carsharing services

States, Canada, Great Britain, and Australia (Howe and Bock 2018; Degele et al. 2018; Raux et al. 2017; Shaheen and Martin 2015; Kim et al. 2015)

Travel behavior is an important factor that impacts users’ adoption of shared mobility services (Abouelela et al. 2022); therefore, we asked respondents about the frequency of their use of twelve modes of transport. The majority of the sample can be described as active PT users, with at least 40% of the sample using PT more than once a week, which is reflected in their subscription to PT weekly and monthly tickets. The subscription to PT services reflects various aspects, such as the users’ loyalty to the service or the high quality of the PT system. Also, younger respondents more actively using PT than their older counterparts, who tend to use more private cars, was observed in other locations as well (Chaisomboon et al. 2020). A considerable percentage of users have access to private car use, as reflected in their car usage. Active travel is evident in the sample, mainly in the form of walking and personal bike, and not much use of shared micromobility modes. We further analyzed the modes used by users versus non-users and also made an assessment by gender; see Fig. 3, Tables 10 and 11. The differences in travel behavior between the genders are well established, where women generally tend to utilize slower transportation modes like public transport and walk more frequently than men. They generally travel shorter distances and have more complex trip arrangements, and are more likely to travel accompanied by children or dependents, facing more challenges related to physical accessibility, safety, and security (Pourhashem et al. 2022; Xu 2020; Tilley and Houston 2016). Gender is a decisive factor in shared mobility use, and specifically in the case of carsharing, as discussed in “Literature review” section. Therefore, we considered the travel behaviour analysis per gender to further investigate these differences and test their impacts on the carsharing use.

Figure 3 shows the frequency of using the different urban modes for users and non-users; to assess the significance of these differences, we performed a chi-square test. From the twelve compared modes, nine were found to have significant differences, and only three modes did not have significant differences, namely walking, tram, and the underground metro. Carsharing users were, on average, more frequent users of all other modes than

non-users (of carsharing services), except for bus(es). In terms of gender, differences in mode frequency were limited and were significant in the case of car use as a passenger and as a driver, shared bike, and taxi; in particular, males used, on average more bikesharing systems and were more often car drivers, as compared to their female counterparts.

Familiarity with carsharing and carsharing use

In this section, we explore the respondent familiarity with carsharing services, and the way they use the service. We asked the users to rank their familiarity with the carsharing service on a four-point scale ranging from: “I do not know about them” to “Very familiar, I know almost everything about them.” Most users (65%) knew about the service, and around one-fifth were very familiar with the service. We asked this question as we believed carsharing use is correlated with user familiarity with them, and we wanted to test the familiarity impact on the different service use aspects as explained in detail in “[Analysis results](#)” section. [Table 9](#) shows the summary statistics for the familiarity with carsharing services for each user and non-users, per gender. Results indicated that users generally had a higher level of familiarity with the service compared to non-users; 88% of users were familiar with the service as compared to 43% of non-users. It is important to highlight that the 12% of the users who were unfamiliar with the service reported that they had used carsharing mainly as passengers. When assessing by gender, there was no significant difference in terms of knowledge, except that males were very familiar with the service, as compared to females.

[Table 9](#) shows the summary statistics of the different aspects of use and familiarity of carsharing services for the different groups; Chi-square tests were used to test the significance of the differences between the different subgroups. The majority of users used the service as passengers, and they used it mainly less than once per week. The major trip purposes are leisure, visits, work, and shopping. Users were asked about the modes they replaced the last carsharing trip with, and the top five modes were the underground, car as a passenger, suburban train, e-hailing service, and car as a driver. These results show potential for negative impacts, as carsharing trips replace mainly PT trips which might increase the vehicle kilometer traveled (VKT) on the roads and, subsequently GHG emissions. We also asked the users to express their willingness to walk to the nearest carsharing vehicle locations, for which 75% of the users specified that they would walk up to seven minutes to the pickup location. We also tested the impact of frequency of use on the willingness to walk, for which no significant results were found. Users’ willingness to walk was uniformly distributed among the different use frequencies. Similar results were observed in fixed-route commercially organized pooled rides (Abouelela et al. [2022](#)).

Modeling results

In this section, we first present the exploratory factor analysis results, after which we present the findings extracted from the four developed hybrid choice models. The aim was to first extract the latent constructs on both user and service-related aspects to carsharing, to then incorporate them and assess their impact on carsharing. In particular, the impact of personality traits and attitudes on knowledge about carsharing, carsharing adoption, and

use, was assessed. The importance of service-related attributes on the choice between car-sharing operators with different payment schemes was also explored.

Exploratory factor analysis

In this sub-section, the exploratory factor analysis (EFA) results are presented, based on which the latent constructs have been extracted, notably for user attitudes; the impact of the extracted factors on carsharing use was then studied. In particular, the factor analysis was conducted for three question groups relating to carsharing operator-related features (“[Car-sharing operator-related features](#)” section), personality traits (“[Personality traits](#)” section), and travel behavior (“[Travel behavior](#)” section).

Carsharing operator-related features

For the first questions group, we asked respondents to rate how important different aspects of carsharing services were to them, on a five-point Likert (Likert 1932) scale that ranges from (1 = not important at all, 2 = not important, 3 = neutral, 4 = important, 5 = very important). Table 10 presents the summary statistics for the ratings of the seven examined aspects of the carsharing service characteristics. The rating summary shows no significant difference between gender groups in the evaluation rate; however, a slight difference in the ranking of the importance of each aspect was observed. Application ease of use was selected as the most critical aspect, while the availability of EVs in the carsharing fleet was rated as the least important factor as per the evaluation order for both genders; the latter was found to be less than neutral for male users with an average evaluation score being less than 3. The rest of the operator-related features were almost the same for both genders, with women’s evaluation scores (in terms of importance) generally consistently higher than males without any statistically significant difference.

When comparing user and non-user groups, interestingly, non-users had, on average higher evaluation scores for the different aspects, except for the availability of different size vehicles, which was the second to last least important aspect based on their rating. Also, application ease of use was the most important service aspect, with a significant difference in rating compared to the next important aspect, app rating. The differences between users and non-users were significant and evident in all aspects, except for service availability in different cities and for app ease of use.

The top part in Table 3 shows the factor analysis results with two main factors representing the main latent constructs and explaining 46% of the total data variability. Factor one can be described as the physical offers, and the second factor as the application-related factors. The results of the EFA for the carsharing operator-related features could possibly reflect on the important dimensions of the service that operators need to focus on to achieve a high level of satisfaction among users.

Personality traits

Understanding personality traits is essential for understanding human travel behavior; yet the impact of such traits on travel behavior is still not well comprehended (Jani 2014). Also, personality might not be a direct influence on travel behavior, but it dictates a certain pattern of behavior (Revelle 2007), and it is more likely to be associated with different

Table 3 Factor analysis model results

I–Carsharing operator-related features	Physical offerings	Application
App ease of use		0.92
App rating		0.60
Availability in airport	0.71	
Availability of different size vehicles	0.62	
Service offers bundles	0.56	
Availability in other cities	0.53	
Availability of electric vehicles	0.51	
Model diagnostics		
Factor loadings	1.82	1.38
Proportion variance	0.26	0.20
Kaiser–Meyer–Olkin factor adequacy: MSA = 0.80		
Cronbach’s alpha = 0.73		
II–Personality traits	Adventurous	Organized
Adventurous	0.82	
Being outdoor	0.51	
Spontaneous	0.61	
Risk taker	0.58	
Variety seeking	0.50	
Efficient		0.70
Punctual		0.46
Model diagnostics		
Factor loadings	1.93	0.76
Proportion variance	0.28	0.11
Kaiser–Meyer–Olkin factor adequacy: MSA = 0.75		
Cronbach’s alpha = 0.6		
III–Travel behavior	Frequent PT user	Frequent micromobility user
Bikesharing		0.75
Shared E-scooter		0.70
Tram	0.68	
Underground	0.85	
Suburban Train	0.73	
Bus	0.69	
Model diagnostics		
Factor loadings	2.43	1.10
Proportion variance	0.35	0.16
Kaiser–Meyer–Olkin factor adequacy: MSA = 0.78		
Cronbach’s alpha = 0.72		

levels of mobility; for example, having an adventurous personality might be associated with a higher level of mobility (Redmond 2000). The middle part in Table 10 presents the summary statistics for the answers pertaining to personality traits for different respondent groups (users, non-users, males, and females). In particular, respondents were asked to specify their agreement with different personality types on a five-point Likert scale (ranging from “Totally disagree”, “Disagree”, “Neutral”, “Agree”, “Totally agree”). After conducting Chi-square tests for assessing the statistical significance in personality traits between different respondent groups (see Table 11 middle part), we found significant differences in personality traits between users and non-users than between the different gender groups (i.e., males and females).

Our initial hypothesis for the EFA was that we would estimate five factors representing the five major personalities, namely risk-taking, loner, ambitious, organized, and lazy. The middle part in Table 3 presents the estimated EFA results for the personality-related questions, for which two main factors were extracted, interpreted as “adventurous” and “organized”. The two factors explain 39% of the data variability. The results of these factors were further used to estimate the impact of these two types of personalities on carsharing use.

Travel behavior

The final set of questions that were analyzed using EFA techniques focused on the frequency of use of the different available modes. For this question, we hypothesized three types of users: PT users, private mode users, and finally, shared mobility users. The bottom part in Table 3 bottom part presents the results of the EFA for the mode use frequency. Two factors were extracted and found to be significant, one for PT users and the other for shared micromobility users; the two factors explained 51% of the variance of the data, and the initial hypothesis was partially correct.

Factors impacting knowledge about carsharing

This model investigates the factors impacting user’s knowledge regarding carsharing. The answer to the question investigating the knowledge about carsharing was set as the dependent variable, which is ordered in nature. The answers to this question were “I do not know about them”; “I have heard about them”; “know about them, but not much details”; “Very familiar, I know almost everything about them”. Ordered HCM model was estimated, and Fig. 4, and Table 4 show the full path diagram and the estimated model results.

Four variables and two latent variables were significant with positive estimated coefficients ($+\beta$), which show that these variables are associated with a higher likelihood regarding higher knowledge about carsharing services: previous use of carsharing, ownership of a driving license, full-time workers, people who live in small households, adventurous persons, and frequent PT users. The thresholds between the different knowledge levels are significant, showing that people understand the difference between the different levels.

The latent variable models can be interpreted as follows: for the measurement model adventurous personality, the positive sign for the estimated coefficient (ζ) for the measurement model part shows that the more the person agrees with the statement, the more likely is this personality type, and the more likely he is to be an adventurous person. The signs of the coefficients of the Structure model part (γ) for males and bike owners show that these variables increase the probability of being an adventurous person compared to the other population group. The other latent variable is the PT frequent user, and the measurement

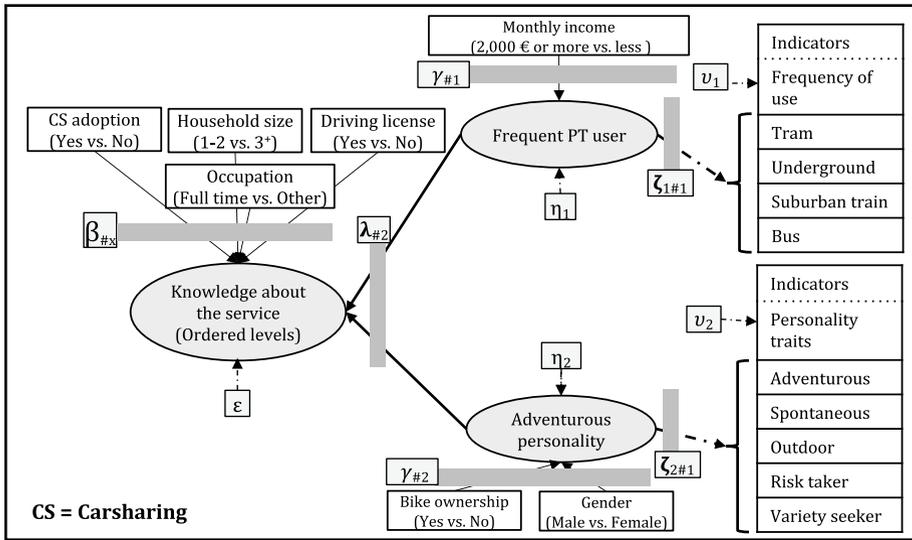


Fig. 4 Full path diagram for the ordered HCM for knowledge about carsharing

model positive coefficient (ζ) sign shows that the higher the answer the more frequently the person uses PT, and the negative sign for the high-income coefficient (γ) shows that high-income people are less likely to be frequent PT users. The estimated model partially answers the first research question (RQ1).

Factors impacting carsharing adoption

This section presents the model results for the model investigating the factors that impact the adoption of carsharing services, and partially answers RQ1. A binary choice and latent variable HCM was estimated to investigate the examined factors. For the subject model, the dependent variable was coded as a binary variable considering responses indicating that they never used carsharing as zero, with the rest of users being coded as 1.

Figure 5 and Table 5 present the full path diagram and the estimation results for the hybrid choice model for carsharing adoption. The estimated model shows that people familiar with carsharing services, with a driving license, who are full-time workers, owners of bikes, with a high-income level, and with a higher education level are more likely to adopt carsharing services compared to other population groups. These significant variables are aligned with the hypothesized profile of shared mobility users, who are in general, wealthier and more educated than the average population. On the other hand, people who have access to a car, live in a small household, and have a subscription to PT tickets are less likely to adopt carsharing services. The two latent variables, frequent shared micro-mobility users (λ_1) and adventurous personality (λ_2), were found to be significant predictors impacting the adoption of carsharing. This model shows that users with adventurous personality have a higher probability of adopting carsharing; such personality was previously (in previous studies) associated with a preference for higher levels of mobility, being outdoor, and disliking routine (Gao et al. 2017; Redmond 2000), which might be the utility provided by carsharing. The other latent variable shows that frequent micromobility users

Table 4 Ordered HCM results for knowledge about carsharing (ordinal variable)

Variable	β	S.E.	<i>P</i> value
Carsharing use (yes vs. no)	2.09	0.15	0.00
Driving license (yes vs. no)	0.68	0.14	0.00
Occupation (full-time vs. other)	0.34	0.14	0.01
Household size (1–2 vs. 3 and more)	0.21	0.13	0.10
LV1: PT user (λ_1)	0.20	0.08	0.01
LV2: Adventurous (λ_2)	0.29	0.08	0.00
Threshold			
I do not know about them—I have heard about them	− 0.93	0.13	0.00
I have heard about them—I know about them, but not details	0.63	0.12	0.00
I know about them, but not details—very familiar with them	3.73	0.17	0.00
Number of observations = 1044			
Latent variable Model			
Structure model (Frequent PT user)			
	γ	S.E.	<i>P</i> value
Income (2000€ or more vs. less than 2000€)	− 0.44	0.08	0.00
Measurement model (Frequent PT user)			
	ζ	S.E.	<i>P</i> value
Tram	1.68	0.12	0.00
Underground	2.68	0.25	0.00
Suburban train	2.00	0.15	0.00
Bus	1.62	0.13	0.00
Latent variable Model			
Structure model (Adventurous personality)			
	γ	S.E.	<i>P</i> value
Gender (male vs. female)	0.14	0.07	0.06
Bike or E-Bike ownership (yes vs. no)	0.12	0.07	0.10
Measurement model (Adventurous personality)			
	ζ	S.E.	<i>P</i> value
Adventurous	2.61	0.24	0.00
Spontaneous	1.37	0.11	0.00
Outdoor	1.13	0.11	0.00
Risk taker	1.43	0.11	0.00
Variety seeker	1.03	0.10	0.00

are more likely to adopt carsharing services in comparison to other population groups. This behavior was also observed in the adoption of other shared mobility services, such as in the case of pooled rides (Abouelela et al. 2022).

The lower part of Table 5 shows the structural equation model of the HCM. The estimation of the latent variable model for the personality part shows that the coefficients of the measurement model part (ζ) is positive, which indicates that the higher the level of agreement with the personality statement questions, the more likely the person to be adventurous. Coefficients of the Structure model (γ) are positive, showing that each of males and bike owners (as opposed to females and non-bike owners) are more likely to be adventurous. The estimation of the second latent variable model shows that the coefficients of measurement models (ζ) are positive, indicating that the higher the frequency of using bike-sharing and/or shared e-scooters, the higher the likelihood to be a frequent shared

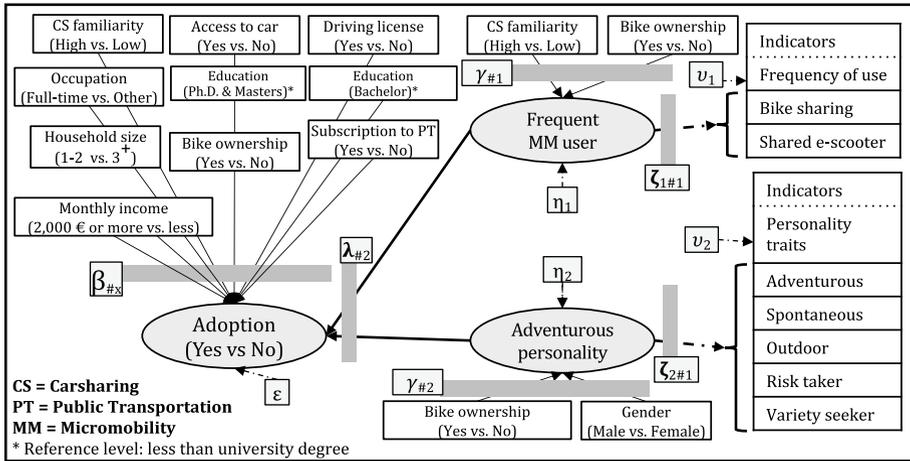


Fig. 5 Full path diagram for the binary HCM for carsharing adoption

micromobility user. Finally, the (γ) coefficient for the Structure model part shows that users who are familiar with carsharing use are more likely to be users of shared micromobility, and car owners are more likely to use micromobility in comparison to other population groups, which matches the general profile of shared mobility users. For both latent models, we did not show the estimation results of the thresholds between the different indicators, as they have no meaning by themselves and only indicate the order of the thresholds.

Factors impacting the shift to carsharing

This model investigated factors impacting the shift from different modes to carsharing. We grouped the modes replaced by carsharing into two groups; the first one being the low-capacity vehicles groups (including cars as a driver, cars as passengers, E-hailing, and Taxis) and the second group being the PT group (with bus, tram, underground, and suburban trains). These observations amounted to 478 users who shifted from the previous specific modes, representing 93% of the total number of carsharing users (515 users). The rest of the observations (37) were removed from the sample used to estimate this model. The dependent variable of the model was coded as a binary variable with the value of one in the case of the shift taking place from a low capacity vehicle (cars as a driver, cars as passengers, E-hailing, and Taxis), the first group, and zero otherwise, similar to the approach adopted by Abouelela et al. (2022). Table 6 shows the model estimation results, and Fig. 6 shows the model’s full path diagram.

The estimated model results show that high-income individuals, who are full-time employed, have access to a car, and are willing to walk less than 5 min to carsharing pick-up locations, are more likely to shift to carsharing from low-occupancy vehicles as compared to the rest of the population, which are in line with the profile of shared mobility users. Only one latent variable was significant in this model, namely the frequent PT users. The negative sign for the latent variable, LV1 (λ), showed that PT frequent users are less likely to shift from low-capacity vehicle trips to carsharing. Similar results were found in the case of pooled rides, where PT frequent users were less likely to adopt shared mobility in the form of pooled rides (Abouelela et al. 2022). The latent variable model shows

Table 5 Binary HCM results for carsharing adoption

Variables	β	S.E.	<i>P</i> value
Intercept	−2.40	0.36	0.00
Carsharing familiarity (high vs. low)	2.03	0.17	0.00
Access to car (yes vs. no)	−0.46	0.20	0.01
Driving license (yes vs. no)	1.10	0.17	0.00
Occupation (full-time vs. other)	0.47	0.20	0.01
Education (Ph.D & Masters vs. less than uni degree)	0.60	0.29	0.02
Education (bachelor vs. less than uni degree)	0.49	0.27	0.04
Household size (1–2 vs. 3 and more)	−0.21	0.16	0.10
Bike or e-Bike ownership (yes vs. no)	0.25	0.16	0.06
PT subscription (yes vs. no)	−0.27	0.21	0.10
Income (2000€ or more vs. less than 2000€)	0.32	0.20	0.05
LV1: Frequent micromobility user (λ_1)	0.28	0.11	0.00
LV2: Adventurous (λ_2)	0.10	0.09	0.13
$\rho^2 = 0.291$	$\rho_{Adjusted}^2 = 0.287$		
Number of observations = 1044			
Latent variable model			
Structure model (adventurous personality)	γ	S.E.	<i>P</i> value
Gender (male vs. female)	0.15	0.07	0.02
Bike or E-Bike ownership (yes vs. no)	0.10	0.07	0.08
Measurement model (adventurous personality)	ζ	S.E.	<i>P</i> value
Adventurous	2.67	0.25	0.00
Spontaneous	1.34	0.11	0.00
Outdoor	1.11	0.10	0.00
Risk taker	1.42	0.11	0.00
Variety seeker	1.02	0.1	0.00
Latent variable model			
Structure model (Frequent micromobility user)	γ	S.E.	<i>P</i> value
Carsharing familiarity (high vs. low)	0.34	0.09	0.00
Bike or e-Bike ownership (yes vs. no)	0.35	0.08	0.00
Measurement model (Frequent micromobility user)	ζ	S.E.	<i>P</i> value
Shared E-scooter	3.76	1.28	0.00
Bike sharing	1.30	0.16	0.00

P values are based on the robust standard errors used to control for heteroscedasticity that might exist

that for the measurement model part, all the coefficients (ζ) are positive, showing that the higher the use frequency, the more likely it is to be a frequent PT user, which is intuitive. The Structure model part shows that people who are familiar with carsharing services are more likely to be frequent PT users, and people who own bikes are more likely to use PT in comparison with those who do not own bikes. The estimated model answers the the remaining part of RQ1.

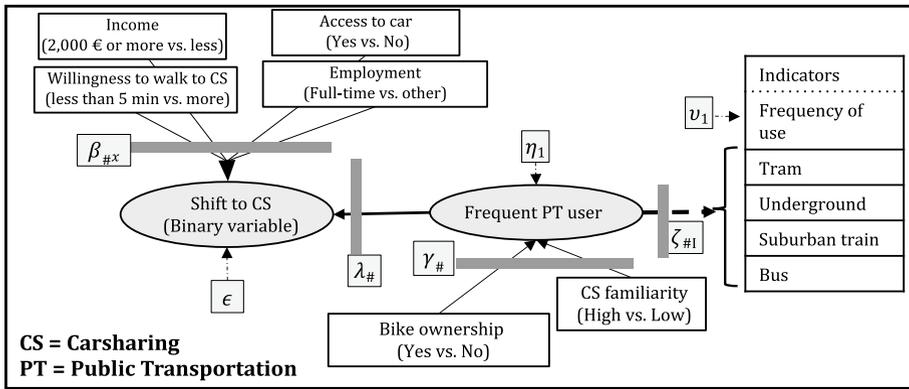


Fig. 6 Full path diagram for the binary HCM for shift to carsharing

Table 6 Binary HCM results for the shift from different modes to carsharing

Variable	β	S.E	P value
ASC	1.04	0.27	0.00
Willingness to walk to carsharing (less than 5 min vs. more than 5 min)	0.32	0.19	0.06
Income (2000€ or more vs. less)	0.45	0.24	0.05
Access to car (yes vs. no)	0.66	0.21	0.00
Occupation (Full-time vs. other)	0.46	0.23	0.05
LV1: Frequent PT user (λ_1)	-0.30	0.12	0.01
$\rho^2 = 0.155$	$\rho^2_{Adjusted} = 0.147$		
Number of observations = 478			
Latent variable Model			
Structure model (Frequent PT user)			
Bike or E-Bike ownership (yes vs. no)	-0.21	0.11	0.05
Carsharing familiarity (high vs. low)	0.27	0.17	0.09
Measurement model (Frequent PT user)			
Tram	2.06	0.21	0.00
Underground	2.57	0.32	0.00
Suburban train	2.26	0.25	0.00
Bus	1.76	0.20	0.00

P values are based on the robust standard errors used to control for heteroscedasticity that might exist

Factors impacting the choice between carsharing operators

This model targeted factors impacting the choice between the different operators with different payment schemes, namely payment per minute or payment per kilometer, which answers the second research question (RQ2). As shown in Fig. 2, six options were available; certainly-A and probably-A, indifferent, probably-B, certainly-B, and “None”. Options certainly-A and probably-A were aggregated to A, the same aggregation was done

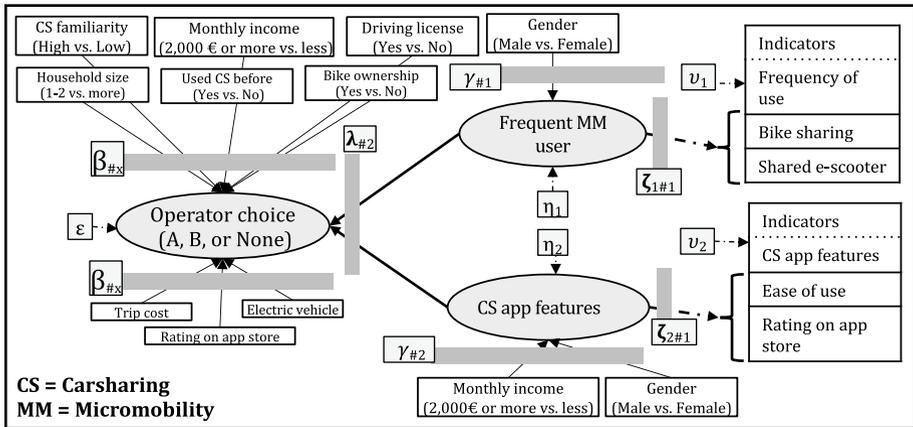


Fig. 7 Full path diagram for the multinomial HCM for carsharing operator choice

for options B, the indifferent option was deleted, and option “None” was kept as the third option, following similar procedures to Abouelela et al. (2021), Fu et al. (2019), Vermeulen et al. (2008).

The indifferent options represented 9.3% of the total answers, and the choices of the remaining aggregated scenarios were distributed as 53.1% for option A, 33.6% for option B, and 4% for the none option. Our hypotheses for the model-building process were that males and people who have adventurous personalities might opt for operator B for its possibility to have cost savings; also, we believe that adventurous users would opt for option B as they were expected to drive faster for cost saving.

Figure 7 shows the full path diagram and Tables 7 and 8 show the estimated model coefficients and parameters for the HCM of the payment schemes. The interpretation of the model results considers the “non-trip” option as the reference level for comparison with other options. The choice experiment tested the significance of four carsharing-related attributes on the choice between the payment schemes; trip cost, access distance, rating on the app, and vehicle engine type, electric or not. All the variables were significant except the access distance. The cost coefficient for option B (pay-per-minute option) was based on the average cost shown in the experiment, and the coefficient of the vehicle being electric or not was generic for both options. Interestingly, app rating was the variable with the highest absolute coefficient value for this group of variables.

The cost coefficient shows that users value the cost of paying per minute to be cheaper than paying per km; we believe that this is most likely due to the fact that there is a chance to pay a lower cost when choosing to pay per minute. Other factors show that app rating is more effective in the choice of option A, compared to option B. Six user characteristics were significant, showing that users with high-income levels, familiarity with carsharing services, valid driving licenses, and who have used carsharing before, were more likely to adopt carsharing compared to other population groups. On the other hand, people who live in small size households and who own bikes were less likely to choose car sharing in comparison to other groups. Finally, the two latent variables were only significant for option B, and they indicated that shared micromobility users were more likely to choose option B, and people who value the importance of the app were more likely to choose option B. We believe that the main reasons for this are that shared micromobility trips are paid per

Table 7 MNL model results for the choice between different carsharing operators

Variable	Operator A (per km)			Operator B (per min.)			None		
	β	S.E.	<i>P</i> value	β	S.E.	<i>P</i> value	β	S.E.	<i>P</i> value
ASC							- 4.77	0.20	0.00
Cost (€)	- 0.37	0.01	0.00	- 0.32	0.01	0.00			
Access distance (m)									
Rating on the app. store (★)	0.41	0.02	0.00	0.30	0.02	0.00			
Electric Vehicle (yes vs. no)*	0.16	0.03	0.00	0.16	0.03	0.00			
Income 2000€ or more (vs. less)	0.34	0.13	0.01	0.41	0.13	0.00			
Driving license (yes vs. no)	0.57	0.13	0.00	0.43	0.13	0.00			
Carsharing familiarity (high vs. low)	0.64	0.11	0.00	0.38	0.11	0.00			
Carsharing use (yes vs. no)	0.79	0.13	0.00	0.83	0.13	0.00			
Household size = 1–2 (vs. 3+)	- 0.19	0.12	0.10	- 0.26	0.12	0.03			
Bike ownership (yes vs. no)	- 0.38	0.11	0.01	- 0.46	0.11	0.00			
LV1: Frequent micromobility user (λ_1)				0.13	0.03	0.00			
LV2: Carsharing app feature (λ_2)				0.14	0.03	0.00			
$\rho^2 = 0.344$									
$\rho^2_{Adjusted} = 0.343$									
Number of observations = 9469									

P values are based on the robust standard errors used to control for heteroscedasticity that might exist

*Generic coefficient for both options

Table 8 Latent variable model results for the choice between different carsharing operators

Latent variable model			
Structure model (Frequent micromobility user)	γ	S.E.	<i>P</i> value
Gender Male (vs. female)	0.291	0.032	0.000
Measurement model (Frequent micromobility user)	ζ	S.E.	<i>P</i> value
Shared E-scooter	1.973	0.131	0.000
Bike-sharing	1.825	0.093	0.000
Latent variable Model			
Structure model (Perceived app importance)	γ	S.E.	<i>P</i> value
Gender: male (vs. female)	- 0.112	0.025	0.000
Income: 2000€ or more (vs. less than 2000€)	- 0.056	0.027	0.041
Measurement model (Perceived app importance)	ζ	S.E.	<i>P</i> value
App ease of use	4.052	0.377	0.000
App rating on app store	1.471	0.046	0.000

P values are based on the robust standard errors used to control for heteroscedasticity that might exist

minute of use; besides, people who value the importance of the app in the service users are more likely to be used to the scheme of paying per minute, which was the original offer for all the shared vehicle services.

Table 8 shows the latent variable models. The first latent variable model, the importance of app-rating, can be interpreted as the coefficient (ζ) for the measurement model being positive, showing that the higher the rating for the importance of app ease of use and the higher the rating on the app store, the more likely the person is to be in this user group. The structural part of the model shows that males and high-income individuals are less likely to be in this group in comparison with the rest of the population. In the second latent variable model, frequent shared micromobility users, the measurement model part coefficients (ζ) shows that the more frequently shared micromobility used, the more likely to be in this group. The structural model part shows that male users are more likely to increase the use of shared micromobility in comparison to female users, which is usually observed in the case of shared mobility services.

It is important to highlight that our initial hypotheses were not significant and personality traits did not impact the choice for the payment scheme, and gender indirectly impacted the choice between payment schemes through the latent variable.

Discussion, limitations, and conclusions

Discussion

In this research, we collected user and carsharing-related data to understand the impact of psychological factors including personality traits, travel behaviour, and attitudes on the knowledge about carsharing, its adoption, and use on the one hand, as well as examine the factors impacting the choice between different carsharing operators. The research was applied to a case study in Munich, Germany, focusing on young users. The collected data shows that carsharing users are young, highly educated males with high-income levels, with full-time jobs, living in small size households, and with a valid driving license, which is aligned with the general profile of shared mobility services and specifically carsharing users (Liao et al. 2020; Namazu et al. 2018). Obviously, the characteristics of carsharing users show the potential for inequitable use problems, wherein population groups, such as low-income and low-education groups, are not frequent carsharing users, which was evident in the collected sample, and revealed by the analysis process and the estimated models. Shared mobility needs a smartphone, digital banking options, and knowledge about the app use to use the service. Such conditions are not always available and add to the inequitable use situation that might result from other conditions, such as service unavailability within reach and service unaffordability (Abouelela et al. 2024). Digitalization therefore becomes a concern as it is often highlighted as a key enabler to sustainable development of cities (Balogun et al. 2020) in general, and to shared mobility in particular (Goehlich et al. 2020). Several strategies could help mitigate this, such as subsidizing the service and offering an alternative to digital access and digital banking options; however, these solutions do not always guarantee success. For example, in Chicago, IL, only 0.05% of shared e-scooter trips were made with non-digital banking options that were provided to help solve the inequitable use problem for shared e-scooter use (Abouelela et al. 2023). While providing alternatives to digital solutions might be plausible in the short-term, addressing concerns of

digital literacy and access might be the only viable long-term solution, so that all population groups can have access to the service and its digital platform.

The collected data analysis showed that users and non-users have distinguished travel behavior with significant differences, which indicates the need for further investigation into how to adjust carsharing service operations to cater to the different travel behaviors and to attract non-users, if possible. Most of the users (40%) indicated that their last carsharing trip replaced PT (underground, suburban train), showing that there is a potential that carsharing might increase the VKT, as it replaces large occupancy vehicles (PT). On the other hand, 35% of users reported carsharing as a replacement for low-occupancy vehicles, including private cars as passengers or drivers and e-hailing, which may reduce the total VKT. The latter could have positive impacts such as reducing energy consumption and resulting CO_2 emissions, and required parking spaces (6t-Bureau de recherche and ADEME 2016; Baptista et al. 2014). More information is required, including the access and egress modes, and the vehicle capacity and occupancy, to better quantify the impacts of carsharing on the VKT; which was not investigated, as it was not the focus of this research.

The responses to the questions regarding familiarity with carsharing services show that there is a proportional relation between carsharing use and knowledge about the service, indicating that to increase the use of such services, more marketing and reach-out plans should be conducted by providers to increase people's knowledge and awareness regarding the service, mainly to target non-users.

The EFA was conducted on the three main question groups (service aspect rating, personality traits, and travel behavior), and each of these groups showed two factors. The first question group related to the carsharing service's important aspects showed two factors: (I) the app-related attributes and (II) physical offers. These estimated factors show the importance of the app-related attributes, which were not examined in previous research, up to the best of our knowledge, and which need more investigation to reach the recommended design by users, as it has a role in impacting service use, as shown in the estimated models. App-related attributes were significant in the preference of paying per minute, but physical attributes were not significant in any of the estimated models, confirming the importance of the app-related aspects of the service.

The second question group is the personality trait group, which showed two distinctive personality traits, (III) an adventurous personality and (IV) an organized personality. Our hypothesis was that an adventurous personality would be more likely to use carsharing services than other types of personality due to the higher levels of mobility and independence provided by carsharing, which fits the characteristics of the adventurous personality (Redmond 2000). The estimated model showed the significance of the adventurous personality in adopting carsharing services and the higher level of knowledge regarding the service.

For the last question group, travel behavior, two estimated attitudes were related to travel behavior; (V) PT frequent user and (VI) shared micromobility user. Both factors indicate a distinguished travel pattern that shapes the adoption and use of carsharing services. Shared micromobility users are likelier to adopt the service and prefer to pay per minute of use, while frequent PT users are less likely to shift from low-capacity vehicles to carsharing. The impacts of the travel behavior latent construct on the use of shared mobility use were evident in the case of pooled rides (Abouelela et al. 2022), showing the importance of accounting for the different travel preferences when planning new services or even integrating them with current services such as PT, and other shared services that could increase the potential of multimodality.

Frequent shared micromobility users, in this case, shared e-scooter and bikesharing, are more likely to adopt other shared mobility services, which highlights the question of

the impacts of shared mobility frequent use on Mobility as a Service (MaaS) platforms adoption or would the availability of all the shared service within one platform increase the use of these services, and increase the possibilities of multimodality, which could be a sustainable outcome. Multimodality is one of the expected positive potential outcome of MaaS, and subsequently increasing the sustainability of the transport system (Ho and Tirachini 2024). It is also to be noticed that carsharing service plays a significant role in MaaS use and utilization, which was observed in the cases of the Augsburg, Germany MaaS trial, where customers of the MaaS bundle utilized their full carsharing allowance and subsequently increase their carsharing use showing the pivotal role for carsharing in MaaS use and utilization (Reck et al. 2021). Also, Keller et al. (2018) observed that car-sharing user have higher intention to use MaaS platforms than the rest of the population.

The estimated models showed that sociodemographics attributes, knowledge about carsharing, and personal attitudes and personality traits play significant roles in carsharing use. The estimated model showed that the attributes that increase the probability of carsharing service adoption are: high familiarity with carsharing service, having a valid driving license, full-time employment, a high education level, high-income level, owning a bike, having an adventurous personality, and being a frequent micromobility user. The results of this model are in line with the general profile of shared mobility users (Le Vine and Polak 2019; Martin and Shaheen 2011a; Alemi et al. 2018; Ahmed et al. 2021; Luo et al. 2019). It is to be noted that the variable with the highest estimated coefficient is familiarity with carsharing services, followed by the availability of a driving license and the (high) level of education. It is clear that knowledge about the service is very important in impacting its adoption, which highlights the role of marketing in service use. Also, shared mobility users are more likely to use such services in different forms. On the other hand, users who have access to a car, users with PT subscription-based tickets, and living in small size households are more likely not to use the service, showing that there is a need to investigate the potential of integrating carsharing services in the PT subscription to increase the service use.

Again, sociodemographic characteristics and attitudes play a significant factor in the shift from different modes to carsharing, where high-income people who are full-time employed, willing to walk for a short period (less than 5 min) and have access to a car have a higher likelihood to shift from low occupancy vehicles to carsharing, while PT frequent users are less likely to do so. This model also shows the significance of sociodemographics and travel behavior in replacing different modes with carsharing services, and it is also in line with the profile of shared mobility users.

When looking at factors impacting the choice between operators with different payment schemes, trip cost, rating on the app store, and availability of electric vehicles were found to be quite significant. App rating was the coefficient with the highest reported value, showing its importance in the choice between different payment schemes. Also, people perceive the payment per minute as cheaper than the payment per km, which is an interesting result showing the preference of users for the payment scheme per minute (the oldest, more common scheme for carsharing payment) over the payment per km with all the other factors being constant. Also, sociodemographics are crucial in choosing between operators, such as high income, driving license, familiarity, and previous use of carsharing services. On the other hand, having a bike and living in a small size household reduce the likelihood of carsharing use. The highest estimated coefficient in this model related to user characteristics is the previous use of carsharing, showing that people who have experience with the service are more likely to choose to pay per minute if all other factors are kept constant. Attitudes also played a significant role, wherein respondents who valued the importance of the app and shared

micromobility frequent users are more likely to use the service and choose to pay per minute of use. These findings highlight the preference for the payment per minute and could be used by operators to increase their demand by focusing on app development and rating.

The answer to the final research question regarding the knowledge about carsharing services emphasized again the importance of sociodemographics and attitudes on the level of knowledge; in particular, previous use of carsharing, availability of a driving license, living in small size households, and full-time employees were more likely to have a higher level of knowledge regarding carsharing service. Service adoption and knowledge about the service were found to be significant in increasing the probability of each other, showing the need to advertise the service to attract more users and to focus on the other social groups that do not have enough knowledge regarding the service and subsequently who do not adopt it. Also, frequent PT users and people with adventurous personalities were more likely to have a higher knowledge regarding the service. Two highlights from these findings are that frequent PT user knowledge about the service should be coupled with encouraging carsharing use as a first-last mile solution that could increase multimodality.

Study limitations and future research needs

This research tries to update the current knowledge regarding carsharing services, using a mix of revealed answer questions and a stated preference experiment. The study comes with limitations, which we believe do not impact the overall research integrity. The main objectives of appraising the limitations are to have a transparent outcome and to help similar studies avoid or consider them in the future. The collected sample was balanced in terms of users versus non-users of carsharing services and in gender, but it was unbalanced for other sociodemographic characteristics, such as income level and education level. On the other hand, shared mobility users are likely to be young and highly educated compared to the average population, which makes the sample acceptable for the purpose of the study, and the sample was not representative of the city's population. The findings should not be directly interpolated or carried out on other social groups. Different attitudes were examined, along with their impacts on the different aspects of carsharing use, but it is important to be noted that attitude and personality traits are hard to quantify and measure. They are essential to understand user preferences for the different aspects of shared mobility use, and they might be more significant and influential in deciding travel behavior in general and shared mobility use.

The used stated preference experience examined only a number of attitudes, travel cost, app rating, electrification of the vehicle, and access distance to the nearest vehicle; other attributes could have been used as well, but this was done on purpose, not to overload the respondents with information that might distract their attention, and to have a simpler experience. The stated preference experiment assumed that the payment by KM is a fixed cost, although this can slightly change in reality, such as in the case of congestion; users could alternate from the original route, the shortest path, causing extra travel distance that would increase the trip cost. The variation of the travel cost ($\pm 25\%$) around the average trip value would cover this possibility. The survey was deployed online, which can create a response bias, as groups with no access to the internet and older populations might not be represented in the sample, but the well established shared mobility user profile shows that they are mostly young and highly educated individuals with access to the internet. The hybrid choice models are not the only way to implement attitudes into discrete models, but we believe that in

this research, they fit the required methodology to answer the main research questions. The personality traits that were estimated via EFA were what the people report, their self-perception on their own personality, but might not be how they are if they had done real psychometric tests. Finally, the assessment of the impact of modal shift (to carsharing) on VKT was not conclusive (see “[Discussion](#)” section), as in most cases carsharing trips replaced PT (likely increasing VKT), at the same time they also often replaced small occupancy vehicles such as cars (possibly reducing thereby VKT). To further investigate this and better quantify the impact, more information would be needed regarding the trips replaced, such as trip distance, vehicle occupancy, and the modes used to access and egress the carsharing services. To project the findings on a larger scale, additional travel behavior data would be essential, so that the modal shift analysis does not only rely on the last trip made, but rather go beyond it to take into account a longer time frame which would encompass the frequency at which such modal shift would occur. As the above was not part of this study, a further in-depth exploration for the VKT analysis is recommended for future research.

As currently carsharing only accounts for a small portion of the total modal share compared to private cars, the magnitude of its impacts is limited (Migliore et al. 2020). Future research could also focus on how extending the service coverage areas, fleet size, and ideally electrifying the fleet could help cities reap the optimum benefits of carsharing (Migliore et al. 2020; Harris et al. 2021; Ye et al. 2021).

It is important to highlight that the survey data was collected during the last waves of the COVID-19 pandemic, and it should be noted that the pandemic conditions inevitably impacted carsharing use and safety perception on different levels. Previous studies on the pandemic impact on carsharing use has been inconclusive, for instance, in Madrid, Spain, carsharing has been perceived by some users as a means to avoid public transport (and therefore as a safer mode), while for others less so, as they replaced it with walking and biking (Alonso-Almeida 2022). A study in Poland showed other findings, in which the pandemic was not a challenge for carsharing users, as it did not hinder their overall use (Gorzelańczyk et al. 2022).

Conclusions

This research investigated the impacts of personality traits and attitudes on the different aspects of carsharing use: adoption, the shift from other modes, the choice between different operators, and finally, the knowledge about the carsharing services. A large sample ($N = 1044$) of young user data was used in the analysis collected from Munich, Germany. The results continue to highlight the importance of the user sociodemographic characteristics in impacting service use and raise questions regarding inequitable service use and adoption. The findings of the estimated econometric models also show the significance of personality traits, travel behavior, and digital service aspects (such as app ease of use and rating on the app store) on carsharing use. These findings also stress the importance of designing user-friendly apps and maintaining good ratings, which can attract more users. Findings also showed that frequent shared mobility users adopt shared mobility in different forms of the service, showing the potential of MaaS in increasing shared mobility use and increasing the potential of multimodality. Finally, the estimated models could be used as a part of broader travel demand models that could estimate the adoption of carsharing and which might be used to quantify the share of the operators based on their payment methods.

Appendix A: Additional analysis

See Tables 9, 10 and 11.

Table 9 Usage and familiarity with carsharing service summary statistics

	Male (%)	Female (%)	Non-user (%)	User (%)
<i>Familiarity with carsharing services</i>				
I do not know about them	13	13	24	2
I have heard about them	20	23	33	10
I know about them, but not much details	49	50	39	60
Very familiar, I know almost everything about them	18	13	4	28
<i>Willingness to walk</i>				
Less than 2 min	12	13	14	11
2–4 min	29	22	22	29
5–7 min	34	35	34	36
8–10 min	21	15	20	17
More than 10 min	10	7	10	8
<i>Type of use</i>				
Yes, as a driver	16	9		
Yes, as a passenger	24	31		
Yes, sometimes as a passenger, and sometimes as a driver	11	8		
Never	49	53		
<i>Frequency of use</i>				
Never	49	53		
Less than once a month	37	34		
1–3 times per month	12	11		
1–3 times a week	1	1		
4 or more times per week	1	0		
<i>Replaced Mode (top 5 modes representing 75% of the users)</i>				
Underground (U-Bahn)	24	26		
Suburban train (S-Bahn)	15	14		
Car as a driver	14	11		
E-hailing (Uber, and similar)	11	9		
Car as a passenger	11	12		
<i>Trip purpose (top 4 purposes representing 80% of users who used Carsharing)</i>				
Leisure (Restaurants, bars, parties)	40	41		
Visiting someone	19	18		
Work	13	10		
Shopping	7	11		

Table 10 Attitudinal questions summary statistics

	User (mean \pm sd)	None-user (mean \pm sd)	Female (mean \pm sd)	Male (mean \pm sd)
<i>Service rating</i>				
App ease of use	4.20 \pm 0.94	4.21 \pm 0.95	4.25 \pm 0.97	4.17 \pm 0.91
App rating	3.54 \pm 1.03	3.74 \pm 1.05	3.68 \pm 1.06	3.61 \pm 1.03
Service offers bundles	3.65 \pm 1.19	3.81 \pm 1.03	3.81 \pm 1.08	3.67 \pm 1.15
Availability in other cities	3.52 \pm 1.18	3.7 \pm 1.16	3.63 \pm 1.19	3.60 \pm 1.16
Availability in Airport	3.60 \pm 1.29	3.71 \pm 1.17	3.82 \pm 1.21	3.52 \pm 1.23
Availability of different size vehicles	3.50 \pm 1.20	3.45 \pm 1.12	3.60 \pm 1.15	3.37 \pm 1.16
Availability of EV	3.02 \pm 1.16	3.23 \pm 1.15	3.30 \pm 1.13	2.98 \pm 1.16
<i>Personality traits</i>				
Adventurous	0.83 \pm 0.85	0.61 \pm 1.01	0.66 \pm 0.97	0.77 \pm 0.92
Anxious	- 0.05 \pm 1.04	0.05 \pm 1.08	0.2 \pm 1.03	- 0.16 \pm 1.06
Being in Charge	0.72 \pm 0.83	0.57 \pm 0.89	0.68 \pm 0.86	0.62 \pm 0.88
Being outdoor	1.06 \pm 0.83	0.84 \pm 0.98	0.99 \pm 0.89	0.91 \pm 0.92
Calm	0.68 \pm 0.98	0.71 \pm 0.95	0.54 \pm 0.98	0.81 \pm 0.94
Creative	0.74 \pm 0.95	0.74 \pm 0.93	0.86 \pm 0.88	0.64 \pm 0.97
Efficient	0.88 \pm 0.85	0.81 \pm 0.83	0.91 \pm 0.83	0.80 \pm 0.85
Independent	1.10 \pm 0.75	0.99 \pm 0.83	1.03 \pm 0.79	1.06 \pm 0.8
Lazy	- 0.13 \pm 1.10	- 0.12 \pm 1.07	- 0.17 \pm 1.04	- 0.09 \pm 1.12
Like to be alone	0.15 \pm 0.99	0.16 \pm 1.11	0.11 \pm 1.02	0.2 \pm 1.09
Optimistic	0.91 \pm 0.85	0.72 \pm 0.95	0.76 \pm 0.89	0.86 \pm 0.92
Participating	0.92 \pm 0.72	0.79 \pm 0.81	0.85 \pm 0.77	0.86 \pm 0.77
Punctual	0.66 \pm 1.14	0.78 \pm 1.05	0.7 \pm 1.09	0.74 \pm 1.10
Risk taker	0.14 \pm 1.02	0.05 \pm 1.08	- 0.02 \pm 1.02	0.19 \pm 1.07
Routines	0.47 \pm 0.97	0.45 \pm 1.00	0.50 \pm 0.98	0.43 \pm 0.99
Spontaneous	0.65 \pm 0.96	0.54 \pm 0.92	0.57 \pm 0.94	0.61 \pm 0.94
Stay close to home	- 0.09 \pm 1.04	0.25 \pm 1.05	0.11 \pm 1.06	0.06 \pm 1.06
Variety Seeker	0.78 \pm 0.79	0.73 \pm 0.86	0.72 \pm 0.8	0.78 \pm 0.85
<i>Mode use frequency</i>				
Bus	2.49 \pm 1.28	2.71 \pm 1.27	2.6 \pm 1.27	2.6 \pm 1.28
Car as driver	1.47 \pm 1.44	0.9 \pm 1.35	0.98 \pm 1.31	1.34 \pm 1.49
Car as passenger	1.70 \pm 1.05	1.42 \pm 1.19	1.71 \pm 1.17	1.44 \pm 1.08
Personal Bike	1.67 \pm 1.54	1.19 \pm 1.48	1.3 \pm 1.51	1.53 \pm 1.54
Suburban train	2.23 \pm 1.26	2.2 \pm 1.37	2.17 \pm 1.32	2.25 \pm 1.31
Shared E-Scooter	0.7 \pm 0.97	0.42 \pm 0.81	0.5 \pm 0.87	0.61 \pm 0.93
Bike sharing	0.54 \pm 0.89	0.43 \pm 0.84	0.39 \pm 0.8	0.56 \pm 0.91
Taxi	0.69 \pm 0.87	0.5 \pm 0.77	0.68 \pm 0.9	0.52 \pm 0.75
Tram	2.16 \pm 1.33	2.11 \pm 1.4	2.13 \pm 1.38	2.14 \pm 1.35
underground	2.97 \pm 1.29	3 \pm 1.37	3.01 \pm 1.34	2.97 \pm 1.33
Walking	3.63 \pm 0.82	3.63 \pm 0.78	3.62 \pm 0.82	3.64 \pm 0.78
E-hailing	0.94 \pm 0.94	0.54 \pm 0.81	0.81 \pm 0.94	0.68 \pm 0.85

Table 10 (continued)

Personality question levels were coded as Totally disagree = - 2, Disagree = - 1, Neutral = 0, Agree = 1, Totally agree = 2
 Mode use frequency levels were coded as Never = 0, Less than once a month = 1, 1–3 times per month = 2, 1–3 times a week = 3, 4 or more times per week = 4

Table 11 χ^2 test results for personality traits

	Users versus None-user		Male versus Female	
	χ^2	'P value'	χ^2	'P value'
<i>Service aspect rating</i>				
Service availability in other cities	6.36	0.17	3.60	0.46
Offers bundles	15.40	0.00*	4.81	0.31
App rating	17.70	0.00*	6.62	0.16
Different size vehicles availability	13.4	0.01*	10.46	0.03*
EV availability	14.80	0.01*	22.00	0.00*
Airport availability	16.40	0.00*	25.73	0.00*
App ease of use	1.68	0.80	11.77	0.02*
<i>Personality</i>				
Efficient	6.20	0.18	5.54	0.24
Independent	6.72	0.15	5.57	0.23
Routines	2.57	0.633	1.94	0.75
Punctual	7.38	0.11	3.35	0.50
Variety Seeking	4.62	0.32	4.70	0.32
Lazy	2.04	0.72	5.01	0.29
Stay close to home	32.6	0.00*	3.06	0.55
Being outdoor	20.00	0.00*	3.26	0.52
Spontaneous	8.77	0.06*	3.72	0.45
Being in charge	12.6	0.01*	4.10	0.39
Participative	10.10	0.03*	5.46	0.24
being alone	12.90	0.01*	6.02	0.20
Optimistic	12.20	0.01*	8.29	0.08
Adventurous	20.90	0.00*	8.29	0.08
Creative	1.48	0.83	15.00	0.00*
Calm	6.89	0.14	21.90	0.00*
Risk taker	4.60	0.33	22.70	0.00*
Anxious	5.52	0.23	31.60	0.00*
<i>Mode use frequency</i>				
Tram	3.28	0.51	3.37	0.50
Walking	6.23	0.18	6.2	0.19
Underground (metro)	7.10	0.13	1.22	0.88
Bus	9.48	0.05*	4.98	0.29
Suburban train	12.00	0.02*	1.5	0.83
Shared-e-Scooter	29.90	0.00*	6.15	0.19
Personal Bike	31.40	0.00*	7.38	0.12

Table 11 (continued)

	Users versus None-user		Male versus Female	
	χ^2	'P value'	χ^2	'P value'
E-hailing	64.00	0.00*	7.41	0.12
Shard Bike	9.97	0.04*	12.7	0.01*
Taxi	18.90	0.00*	14.5	0.01*
Car as a passenger	43.10	0.00*	16.2	0.00*
Car as as driver	71.50	0.00*	18.2	0.00*

*Significant difference with minimum 95% significance level

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Declarations

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