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A latent class approach to explore shared mobility among older people in Midsized Dutch inner cities

Fatemeh Torabi Kachousangi [a,*], Yashar Araghi [b], Niels van Oort [a], Serge Hoogendoorn [a]

[a] Delft University of Technology, Department Transport & Planning, Smart PT Lab, Delft, the Netherlands
[b] TNO, Netherlands Organisation for Applied Scientific Research. The Hague, the Netherlands

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ABSTRACT

Car dominance in urban landscapes poses environmental, health, and congestion challenges. This comprehensive study examines the potential of shared mobility in car-free areas. Specifically, it investigates the mobility behaviour of inner-city older adult residents (50 +), traditionally heavy car users through a case study of small-medium-sized Dutch cities and a stated preference experiment.

This study applies a Latent Class model to analyse the heterogeneity in passengers' preferences, identifying four distinct groups: *Price Sensitive & Private Car Enthusiasts, Time-Conscious Travellers, Pro-Cycling & Conventional travellers, and Micromobility Enthusiasts*. The model predicts class membership based on travel behaviour data from the stated choice experiment and examines the role of key factors such as travel cost, travel time, and walking distance in shaping mode choices across five transport options: bike, e-bike, e-scooter, e-Brommobiel, and e-car. The findings reveal that a significant portion of travellers recognise the value of shared mobility options in reducing private car dependency, underscoring the need for targeted interventions to address barriers and enhance accessibility to promote shared mobility adoption. Based on these distinct passenger segments, the study proposes specific policy measures that not only enhance transport planning but also address existing challenges and user concerns in sustainable urban mobility.

1. Introduction

Worldwide, motorised traffic is projected to grow from one billion vehicles in 2011 to two billion by 2050, driven by income growth and population increases (OECD/ITF, 2012). While private cars theoretically enable fast travel, they often dominate urban space, causing congestion and reducing urban liveability (Hardt & Bogenberger, 2019). Moreover, as motorized vehicles continue to dominate urban landscapes, space for pedestrians, cyclists, and public transport infrastructure remains limited, exacerbating accessibility challenges. Additionally, private cars dominate public spaces, for instance, in the Netherlands, cars occupy 55 % of street space in major cities but remain parked 96 % of the time (Jorritsma et al., 2021; van Liere et al., 2017).

This inefficient use of space underlines the urgency for cities to implement space-efficient measures to tackle growing congestion and lack of space while enhancing accessibility (van Marsbergen et al., 2022). The need to discourage car use and transition to sustainable transportation systems has gained recognition among scholars, governments, and health organisations (Green Deal Autodelen II, 2022; van der Linden et al., 2024). While technological advancements like electric vehicles help mitigate environmental concerns, they do not address challenges related to spatial efficiency and congestion (Litman, 2014).

To tackle these issues, many cities are transforming some areas partially or entirely to car-free neighbourhoods, particularly in their inner-city centres or popular commercial and shopping areas (Gärling and Loukopoulos, 2007; Nieuwenhuijsen & Khreis, 2016). These car-free developments aim to reduce congestion, enhance transport accessibility, and create safer and more livable urban spaces by expanding cycling infrastructure, establishing pedestrian zones, and increasing green areas (Nieuwenhuijsen & Khreis, 2016). While reducing car dependency is a key measure to create more space in urban areas, it is crucial to ensure inclusivity and equitable mobility access, particularly for vulnerable populations, particularly older adults, who are more likely to face physical limitations, digital barriers, and greater reliance on private vehicles or public transport.

* Corresponding author.
E-mail addresses: F.TorabiKachousangi@TUDelft.nl (F. Torabi Kachousangi), yashar.araghi@tno.nl (Y. Araghi), N.vanOort@TUDelft.nl (N. van Oort), s.p.hoogendoorn@tudelft.nl (S. Hoogendoorn).

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While much of shared mobility literature focuses on younger, tech-savvy users, a growing body of research highlights the distinctive needs and behaviours of older adults in mobility system. Older people are not a homogeneous group, and their mobility choices are shaped by a variety of factors such as health, lifestyle, car availability, and attitudes toward transport. As Haustein and Siren (2015) demonstrate, segmentation approaches can reveal meaningful subgroups among older adults, ranging from highly mobile individuals to those facing significant transport disadvantage. Understanding these differences is essential to designing inclusive mobility strategies that address both actual and perceived mobility limitations.

The mobility challenges for older adults go beyond physical accessibility and include affordability and digital exclusion. Income disparities and car ownership play a crucial role in determining public transport affordability (Bon et al., 2025), often reinforcing car dependency among specific groups. Additionally, as cities increasingly adopt digital mobility services, new accessibility barriers are emerging. Nearly 75 % of public transport and car users report that traveling has become significantly more difficult without a smartphone, highlighting a growing digital divide in mobility access (Durand et al., 2024). While digital tools enhance convenience for many, individuals with lower digital literacy or limited smartphone access—particularly older adults and those unfamiliar with digital platforms—face additional obstacles in navigating transport systems. If left unaddressed, these digital disparities could further marginalize certain populations, restricting their mobility options and deepening transport inequalities (Durand et al., 2024).

Although non-motorized transport modes, such as cycling and walking, have been essential alternatives for ensuring accessibility in car-free city centres (Szarata et al., 2017; Gascon et al., 2015), shared mobility and micro-mobility have emerged as a space-efficient and flexible alternative to private car use that improves urban accessibility and reduce reliance on motorized transportation (Handy et al., 2014). Additionally, shared cars offer a practical solution for occasional car use while reducing overall car dependency (Kolleck et al., 2021; Nijland & van Meerkerk, 2017).

Studies indicate that shared mobility adoption among older adults remains low, faces barriers such as digital illiteracy, unfamiliarity with technology, and physical limitations (Kim et al., 2021; Van Kuijk et al., 2022). Notably, public transport users report higher digital literacy than car users, despite no significant differences in education or age, suggesting that digital skills play an overlooked role in mode choice (Durand et al., 2024). Research on shared mobility services has largely focused on young, urban populations, leaving a gap in understanding how older adults and residents of smaller cities perceive and engage with these services (Dill and McNeil, 2021). Given that older adults constitute a significant portion of inner-city residents, addressing these accessibility barriers is crucial to ensuring that car-free zones remain inclusive and equitable. The segmentation of older adults, as explored by Haustein and Siren (2015), can help uncover specific travel needs and guide the design of targeted mobility policies.

To encourage the adaption of shared mobility solutions, cities are implementing measures such as limiting car ownership and reducing parking availability to alleviate congestion, improve safety, and promote walkability in city centres (Baehler, 2019; Melia et al., 2010; Cathkart-Keays, 2015). However, these initiatives often face strong societal resistance (Pojani et al., 2018), particularly from groups reliant on private vehicles (Cathkart-Keays, 2015; Baehler, 2019; Poudenx, 2008; Jeekel, 2013). A key challenge lies in the digital nature of shared mobility services, which excludes individuals lacking digital literacy or smartphone access (Durand et al., 2021; Durand et al., 2024; Pangbourne et al., 2020). As a result, older adults and non-tech-savvy users are at a disadvantage, further limiting the inclusivity of these transport options.

Younger individuals tend to adopt shared micro-mobility services more readily due to their digital proficiency and flexible mobility habits (Böcker & Anderson, 2020; Chen et al., 2020; Tao & Pender, 2020; Alonso-González et al., 2020; Eren & Uz, 2020; Geržinič et al., 2022). In contrast, older adults may be hesitant due to unfamiliarity with technology, cognitive decline, and physical limitations (Kim et al., 2021; Van Kuijk et al., 2022). Integrating all socio-economic groups into the urban mobility transition is crucial for broadening acceptance (Geurs & Münzel, 2022). Thus, understanding these barriers, particularly among older adult non-users, is essential for promoting equitable shared mobility solutions. Addressing these gaps is critical for promoting shared mobility in smaller urban areas where car dependency remains high.

This study determines the factors influencing the (un) willingness to use shared mobility among older adult travellers (50 +) in small- to medium-sized Dutch cities. We use a discrete-choice latent class model (LCM), which categorises individuals into latent classes based on shared characteristics and similarity in their stated preferences for shared mobility options. This approach captures unobserved heterogeneity and supports the development of inclusive, age-sensitive transport strategies—especially critical as cities move toward car-free zones.

We collect data from a diverse sample of older adults and apply a discrete-choice LCM to segment them based on stated preferences. We then analyse the socio-demographic of each group post-estimation. This segmentation provides valuable insights for designing targeted policies tailored to the specific needs of each segment.

By gathering data from this group, the research aims to provide actionable insights for promoting sustainable transportation options in underexplored demographic groups. Section 2 outlines the study's methodology, detailing the case study across 45 small- to medium-sized Dutch cities, the survey approach (2.1), and the stated choice experiment used to analyse user preferences. Section 3 presents the data analysis related to current journeys, followed by Section 4, which discusses choice modelling results and heterogeneity in transport mode preferences (4.1). Finally, Sections 5 and 6 provide a discussion of key findings, policy recommendations, and concluding remarks.

2. Research methodology

To investigate how shared mobility services can effectively reduce private car use in car-free inner cities, this research employs a stated choice experiment to reveal people's preferences for adopting such services. Since car-free zones have not yet been widely implemented in the Netherlands, and shared mobility modes are still emerging, a choice experiment allows us to present hypothetical scenarios.

Additionally, while car-free initiatives have primarily been studied in larger cities, smaller and medium-sized cities—often more car-dependent due to less developed public transport networks—have received less attention. This study addresses this gap by exploring the potential of shared mobility in car-free areas. This approach enables us to examine potential user preferences in a future context where these car-free areas and new mobility options are more prevalent. We selected 45 small to medium-sized cities across the Netherlands to provide a diverse and representative sample, ensuring the findings apply to a range of urban environments. The cities, with populations ranging from 33.880 to 133.133, are in the provinces of South Holland, North Holland, North Barabant, Utrecht, Overijssel, Gelderland, and Limburg, as shown in Fig. 1. A full list of the 45 cities, along with their corresponding provinces, population, land area, and postal codes, is provided in Appendix A for reference.

The study examines individuals' attitudes toward different modes of transportation in small and medium-sized Dutch cities. In this section, we describe the research setup.

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Fig. 1. Overview of cities as case studies.

2.1. Survey overview

To identify the factors influencing travel behaviour and observe current and future mode choice decisions, we conducted an online survey consisting of two parts: 1) previous experiences, including experiences with shared modes, everyday journeys, and socio-economic characteristics of residents at these inner-cities, and 2) stated choice experiments. This survey was conducted by a survey panel, PanelClix, recognised for its high standards in market research. This panel actively distribute surveys to a diverse range of participants, including some with limited digital access. However, as the survey was conducted online, certain digitally excluded groups may still be underrepresented. The survey was available in both English and Dutch and was initiated between April 2 and April 14, 2024.

Since we are interested in the choice preferences of older adults, defined in this study as individuals aged 50 and above, encompassing the later stages of middle age and beyond— the survey was only accessible to inner-city residents within this age group. The survey began with a brief explanation of the study's purpose and some related information.

Part 1: Past Preferences Survey

This survey aims to capture car dependency, the level of familiarity of residents with shared modes, and their socio-economic characteristics. Firstly, the questionnaire covers aspects such as possession of a driver's license, car ownership, and car dependency. Then, respondents were asked about their experience of shared modes and willingness to opt for them over private cars. The survey delves into respondents' recent trips approximately 10 km distance from the inner city, exploring details like transport mode, trip purposes, distance, and travel companions.

Part 2: Stated Choice Experiment

Choice models based on the random utility maximisation (RUM) theory are widely used to study individual travel behaviour (McFadden, 2000; Ortúzar & Willumsen, 2001; Train, 2003). While some studies have focused on travellers' attitudes toward shared modes (Torabi Kachousangi et al., 2022; Van Dijk et al., 2022), our focus is on understanding behaviour heterogeneity using revealed choice data.

This study adopts the methodological framework originally proposed by McFadden (1986) and further developed by Kamakura & Russell (1989) and Boxall & Adamowicz (2002). By analysing stated preferences, this approach enables a deeper understanding of differences among older adults in their willingness to adopt shared mobility services.

This study employs a discrete-choice Latent Class Model (LCM) to analyse passenger decision-making and segment individuals based on shared preferences. The model consists of two components:

- The choice model, which estimates the probability of selecting a shared mode from a set of alternatives, which assumes that passengers choose the option offering the highest perceived utility.
- The class membership model, which determines the probability of an individual belonging to a specific latent class, where each class is

characterised by distinct taste parameters (Swait, 1994; Boxall & Adamowicz, 2002).

Unlike mixed logit models, which assume continuous distributions for taste parameters, LCM assumes a discrete distribution, categorising individuals probabilistically into a fixed number of latent classes (Araghi et al., 2016).

In our application, class membership is estimated based only on the observed choices from the sated choice experiment to estimate class membership and explain heterogeneity in travel choices. This provides a deeper behavioural understanding of preference variations, making the identified classes more actionable for policymakers and industry stakeholders (Araghi et al., 2016).

We explored four common shared transportation modes, including 1) shared bike, 2) shared electric bike, 3) shared electric scooter, and 4) shared electric car, and studied the potential impact of the shared e-Brommobiel on the choice of those aged 50 and above. While not yet part of a shared mobility system, this small-size vehicle may promise a comparable option to cars. In addition, three attributes are considered, including 1) Total Travel Cost (return trip, in €), 2) In-Vehicle Travel Time (minutes), and 3) Walking Distance to shared modes (minutes).

The selection of alternatives and attributes are all based on their prevalence and importance in the literature, especially in studies targeting older populations and shared mobility choices. Attribute levels were determined using a combination of Dutch market-based data and behaviour realism, as shown in Table 1. Levels were pre-tested in a pilot survey and refined through an efficient design procedure in Ngene, with the aim of balancing realism and statistical variance.

- Total Travel Cost levels were based on public pricing from Dutch operators such as OV-fiets, Felyx, and Greenwheels. For the Brommobiel, we assumed that the price should fall within the average range of shared scooter and car prices.
- In-Vehicle Travel Time was calculated based on average various modal speeds over a 10 km one-way trip.
- Walking Distances to shared modes were set to reflect typical accessibility ranges for shared mobility vehicles in Dutch cities, while remaining feasible for older adults.

Considering the age of the participants as well as the complexity of the choice experiment, the participants were visually explained and informed about the car-free area concept and how the choice experiment works by giving an example at the beginning of this part. They were presented as follows:

"*Imagine that the City Centre, where you live, is a car-free area, which means you are not allowed to bring and use your private car in this area. Instead, the below-shared modes are available at stations nearby, while only shared electric cars and shared electric Bromobiels (small cars) are located at the border of the City Center. You must walk and take one of these transport modes for your trip, as shown in* Fig. 2.

*You will receive eight different choice sets, each including different shared transport modes. Each vehicle has its own **total travel cost**, including the staying time, **total travel time in that vehicle** regardless of the staying time, and the **walking distance** to access the shared modes. For instance, if travelling with a shared (e) scooter takes 40 min and 10 euros, it means each way takes 20 min and 5 euros.*

Suppose you would have a return trip to that destination outside of the City Centre and back home (approx. 10 km for one way and in total approx.20 km). But you cannot use your private car for this trip, and you must compare different shared modes and choose one, even if it is not your ideal.".

Table 1
Overview of attributes and attribute levels used in the stated choice experiment.

Attribute	Attributes levels	
Travel cost for a return trip – shared bike	€ 6	€ 8
Travel cost for a return trip – shared E-bike	€ 8	€ 9
Travel cost for a return trip – shared E-scooter	€ 9	€ 10
Travel cost for a return trip – shared E-Brommobiel	€ 10	€ 12
Travel cost for a return trip – shared E-car	€ 12	€ 14
In-vehicle total travel time – shared bike	55 min	65 min
In-vehicle total travel time – shared E-bike	45 min	50 min
In-vehicle total travel time – shared E-scooter	40 min	45 min
In-vehicle total travel time – shared E-Brommobiel	30 min	35 min
In-vehicle total travel time – shared E-car	20 min	25 min
Walking distance to access shared bike	2 min	4 min
Walking distance to access shared E-bike	4 min	6 min
Walking distance to access shared E-scooter	4 min	6 min
Walking distance to access shared E-Brommobiel	8 min	12 min
Walking distance to access shared E-car	8 min	12 min

To determine the appropriate number of choice sets, we first conducted a small-scale test pilot with a limited sample of 25 respondents. This pilot study followed an orthogonal design, which does not require prior knowledge of the parameters but ensures that all attribute levels are evenly represented. The responses from this pilot were analysed to generate preliminary estimates (priors) of the choice model coefficients. These priors were essential for developing an efficient design. An efficient design was subsequently created using Ngene software to improve estimation efficiency compared to a purely orthogonal design. Given the number of attributes (three) and alternatives (five) included in the study, the efficient design process determined that 16 choice sets would be optimal. This number strikes a balance between ensuring robust statistical estimation of preferences while avoiding excessive fatigue among respondents. A larger number of choice sets could lead to disengagement and reduced response quality, whereas fewer choice sets might limit the ability to capture reliable preference estimates.

By leveraging the priors obtained from the pilot study, the final efficient design was structured to maximise the reliability of the collected data in the main survey. This approach ensures that the choice sets are not only statistically sound but also practical for respondents, leading to more accurate insights into shared mobility adoption in car-free urban environments.

Participants were assigned eight choice sets randomly from 16 choice sets to make the survey more practical and manageable while still capturing sufficient data for analysis. They were instructed to recall their recent trips (approx. 10 km distance), compare alternatives, and choose their primary mode for their return trip from home to a destination in/outside the city centre, considering the characteristics of these transport modes, shown in Fig. 3.

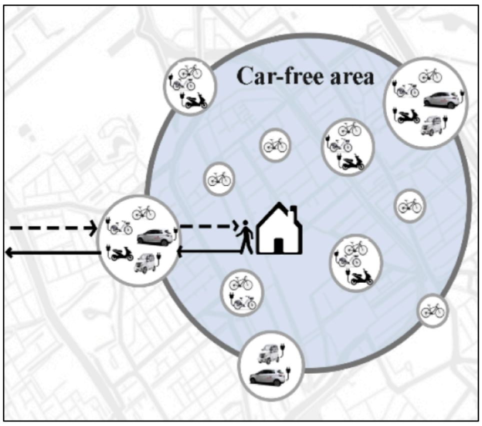
R software was used to perform the maximum likelihood estimation of the discrete choice model. In the next section, the results of the models are presented and discussed.

3. Data analysis related to the current journey

In this section, we present some general descriptive statistics about the past trip and demographic characteristics on using private cars and shared modes, presented in Table 2. In total, 497 respondents participated in the survey. Seventy-nine respondents were excluded from the data set due to not finishing the survey; the remaining 418 respondents formed the data set in this study. This equals to 3344 complete choices.

The data includes demographic factors such as age, gender, family status, education level, and income. It also examines health, private car use, reasons for using cars, shared mobility experiences, and current trip variables. The analysis aims to provide critical insights into the capacity of respondents to use shared modes.

It is worth noting that the sample was designed to be broadly representative of the Dutch older adults population (50 +). Participants were selected from 45 cities across the Netherlands, ensuring geographic diversity and capturing a wide range of socio-economic and urban–rural contexts. This approach enhances the likelihood that the sample reflects the characteristics and behaviours of the target demographic at a national level.



	· Renting for a short-term use · Located in the car-free area · 2-4 minutes walking distance from your house.
Shared electric bike	· Renting for a short-term use · Faster than a normal bike · Located in the car-free area · 4-6 minutes walking distance from your house
Shared electric scooter	· Renting for a short-term use · Moves in bike lanes, top speed around 45 km/h · Located in the car-free area · 4-6 minutes walking distance from your house
	· Renting for a short-term use · Microcar with a top speed of around 45 km/h · Moves on roads, not highways · Located on the border of the City Centre · 8-12 minutes walking distance from your house
Shared electric car	· Renting for a short-term use · Moves on roads and highways · Located on the border of the City Centre · 8-12 minutes walking distance from your house

Fig. 2. Overview of the Car-free area concept (left figure) and the alternative characteristics (right figure).

A2	Shared bike	Shared E-bike	Shared E-scooter	Shared E-Brommobiel	Shared E-car
Cost for a return trip	6 euro	8 euro	10 euro	10 euro	14 euro
In vehicle total travel time	65 min	45 min	40 min	30 min	25 min
Walking distance to shared modes	2 min	6 min	4 min	12 min	8 min

o Shared bike o Shared E-bike o Shared E-scooter o Shared E- Brommobiel o Shared E-car

Fig. 3. Example of a choice set demonstrated to respondents in the survey.

3.1. Demographic analysis

Regarding the socio-demographic characteristics of the sample, Table 2 shows that it contains higher shares of 50–69 years (66 %), male (58 %), less formally educated (53 %), and low to medium economic level 71.000 ≥ euro (55 %) users who are mostly household with at least two adults (66 %), and single (28 %). Regardless of age, they mostly are fully physically mobile (75 %), and only 19 % have mobility limitations due to their age concerning walking (65 % people), cycling (42 % people), and driving (28 % people), respectively.

3.2. Mobility behaviour and preferences

The data highlights a strong dependence on private car use. Car usage frequency shows that 29 % use their cars four or more days per week, while 40 % use them one to three days per week, highlighting room for alternatives.

Moreover, weather conditions and the nature of the trip heavily influence car use. Specifically, 45 % of respondents use a car in rainy or cold weather, and 61 % use it for long trips. Travelling with elderly individuals or children (34 %) is also a significant reason for car use. Interestingly, 23 % of respondents always use a car, while only 1 % never do.

3.3. Shared mobility experience

Despite high familiarity (84 %), shared mobility adoption remains low, even though it has been identified as a potential alternative to private vehicle ownership in urban transport research. Most respondents reported either never using shared transport or only trying it once or twice, with only a small percentage (1–3 days per month) using it regularly (Fig. 4). A key barrier is the strong preference for the comfort and convenience of private cars (61 %), reinforcing the perception that shared mobility is less convenient. Reliability issues, such as inconsistent service and availability (27 %), further deter adoption, highlighting the need for operational improvements to build user trust.

Table 2
Sample statistics with different socio-economic variables (n = 497).

Socio-economic variable	Category	Share sample
Age	50–59	30 %
	60–69	36 %
	70–79	29 %
	80≤	5 %
Gender	Male	58 %
	Female	42 %
Family status	Single	28 %
	Households with at least two adults	66 %
	Household with 1 ≤ children the age 12 years old or younger	2 %
	Household with 1 ≤ children with the age of 13 up to 17 years old	4 %
Education level	Less formally educated (under HAVO and VWO)	53 %
	Moderately educated (HBO / WO (Bachelor's degree))	24 %
	Highly educated (HBO / WO Master's or doctoral degree)	23 %
Income (Total family gross annual)	Less than € 42.400	33 %
	Between € 42.400 and € 71.000	22 %
	Between € 71.000 or more	22 %
	Won't say	23 %
Health ability	I am fully mobile (physically able)	75 %
	My mobility is limited (due to age, pregnancy, etc.)	19 %
	I am not a mobile	6 %
Health limitation	Walking	65 %
	Cycling	42 %
	Driving	28 %
	Travelling by public transport	32 %
Private cars use variable		
Having driving license	Yes	86 %
Having a car	Yes	81 %
Average use of car	4 days per week or more	29 %
	1–3 days per week	40 %
	1–3 days per month	16 %
	1–11 days per year	10 %
	Never	5 %
Reasons for using a car	Rainy/cold weather	45 %
	If I have heavy, oversized and/or a lot of bags (s)	1 %
	When I travel with people who are old and children	34 %
	When I have a long trip	61 %
	Always	23 %
	Never	1 %
Shared modes experience variable		
Familiarity with shared mobility concept	Yes	84 %
	No	16 %
The main reasons for using shared mobility	1) Cost savings compared to private ownership	14 %
		%
		%
		%
		%
		%
		%
		%
		%
		%
	2) Environmental consideration: carbon footprint reduction	14 %
	3) Comfort: convenient and flexible transport	12 %
		%
		%
		%
		%
		%
		%
		%
		%
		%
	4) Sustainability: preference for sustainable options	10 %
	5) Skip the parking and traffic troubles	9 %
	6) Lack of private vehicles	9 %
Main reasons for not/less using shared mobility	1) Comfort: preferred the convenience of a private vehicle	61 %
		27′5%
	2) Reliability: issues with services and availability	%
		%
		%
		%
		%
		%
		%
		%
		27 %
	3) Cost: shared options are too expensive.	25 %
	4) Cleanliness: worries about shared vehicle hygiene	19 %
	5) Lack of Awareness: Limited knowledge of shared options	12 %
	6) Technology Challenges: Limited familiarity with booking or using shared transport apps/device	9 %
Current trip variable		
Main mode	Car as driver	51 %
	Car as passenger	17 %
	Train/metro/bus/tram	16 %
	Two wheels vehicles	12 %
	Walking	2 %
	Shared modes	0 %
Purpose	Social/Recreational/Visit	54 %
	To work	19 %
	Shopping	14 %
	Personal care	6 %
With whom	With one or more adults	50 %
	Alone	49 %

Current transportation patterns further illustrate this trend. When asked about their most recent trip (approximately 10 km) from home to a destination outside the city centre, respondents overwhelmingly reported car use as their primary mode, either as drivers (51 %) or passengers (17 %). Public transport usage (train/metro/bus/tram) stands at 16 %, while two-wheeled vehicles account for 12 %. Notably, no respondents reported using shared mobility services, reinforcing the findings that adoption remains minimal despite familiarity. Trip purposes varied, with visit/social/recreational activities (54 %) being the most common, followed by commuting to work (19 %) and shopping (14 %).

Cost perceptions are divided, with 25 % seeing it as a barrier, while others cite cost savings (14 %) as a motivator. Hygiene concerns (19 %) also impact usage, likely amplified by post-pandemic sensitivities. Additionally, limited awareness (12 %) and technological challenges (9 %) hinder adoption, suggesting a need for improved user education and more accessible platforms. On the other hand, environmental considerations (14 %) and skipping parking or traffic hassles (9 %) appeal to some users but remain underemphasised in promotional efforts.

Accessibility also plays a critical role- users prefer shorter walking distances for micro-mobility options (within 2 min), while electric cars remain attractive even at longer distances (5–10 min), as shown in Fig. 4. These findings indicate that addressing convenience, reliability, and awareness could enhance shared mobility adoption while also making it a viable alternative for current trip behaviours.

The findings indicate a strong dependence on private car use among older adults, despite a high level of familiarity (84 %) with shared mobility. While cost savings and environmental considerations motivate some individuals, shared mobility adoption remains minimal, suggesting that perceived barriers outweigh potential benefits. Addressing key concerns could enhance adoption rates and make shared mobility a

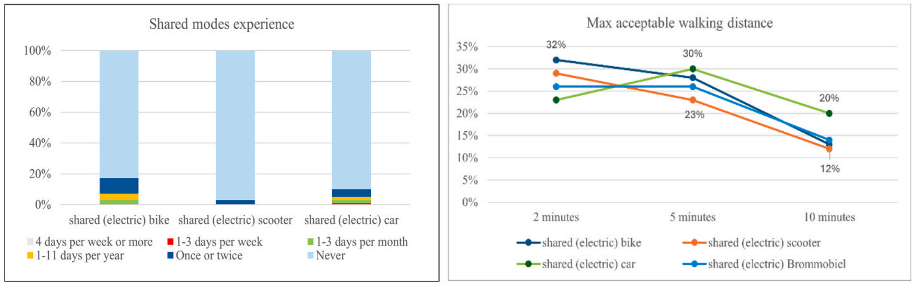


Fig. 4. Shared mobility experience (left) and maximum acceptable walking distance to access shared mobility.

more viable alternative.

4. Choice modelling results and data analysis

In this chapter, we discuss the results of the choice modelling experiments using the data collected.

To provide a benchmark and demonstrate the added value of using a Latent Class Model (LCM), we first estimated a basic Multinomial Logit (MNL) model as a baseline. The MNL assumes homogeneous preferences across all individuals and does not account for unobserved heterogeneity. Table 3 presents the parameter estimates and model fit statistics for the MNL model.

The results show that the MNL captures general trends (e.g., negative preferences for e-Brommobiel and e-scooters, and a significant cost sensitivity), but the overall model fit is limited. The log-likelihood at convergence is −4707.09, with an adjusted rho-squared value of only 0.1241. These values suggest that while the MNL offers a basic explanation of behaviour, it does not capture the variation in preferences observed across different population subgroups.

To capture the heterogeneity in user preferences and move beyond the limitations of the MNL model, we estimated a Latent Class Model (LCM) using the Apollo package (Hess and Palma, 2023). LCM allows for preference variation across latent segments by probabilistically assigning individuals to different classes with distinct utility structures.

To determine the optimal number of latent classes, we considered the ρ^2 values along with the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These information criteria balance model fit and parsimony (Swait, 1994). In addition to these statistical measures, we also evaluated the interpretability of the results to ensure meaningful segmentation.

To determine the optimal number of latent classes, we estimated multiple models, ranging from a one-class specification (essentially an MNL model) to a five-class model. The model fit indices for these estimations are summarised in Table 4. The 4-class model is the best choice, as indicated by the lowest Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), the highest explanatory power (ρ^2), and the best log-likelihood improvement. The 2-class and 5-class models performed worse, while the 3-class model failed to improve beyond the null model. Given its superior balance of fit, complexity, and interpretability, the 4-class model is the most appropriate selection.

Table 5 displays the parameter estimates for the four latent segments, each representing a different pattern of preferences among respondents. To assign different respondents in the dataset to one of the 4 latent segments of the 4-class model, we used the mean probability values. These values indicate the probability of each being part of any of the latent segments. Each respondent gets assigned to a class with the highest probability of being likely to be similar to other respondents in that given class. Hence, we observe that Class 1 contains the highest share (37.14 %) and Class 4 the lowest (16.45 %). Some classes are more prevalent in the sample than others, implying differences in how groups of respondents make their choices among shared modes. We example the names given to the classes based in the estimated parameter values in detail in section 4.1.

This Latent Class Model shows a significant improvement in model fit. The log-likelihood improves from LL (start) −5381.96 to LL (final) –2223.25, demonstrating a much better explanation of choices than the baseline models. The model's adjusted rho-squared values (0.5811 vs equal shares, 0.5251 vs observed shares) confirm its strong performance. The improvement in fit from the MNL model to the LCM clearly demonstrates the added value of capturing unobserved preference heterogeneity among older adults in shared mobility choices. Detailed class-specific parameters are provided in Section 4.1.

Table 3
Parameter estimates and model fit of the discrete-choice Multinominal Logit model.

Main effects	MNL	
	Estimate	**t-value**
ASC_bike	0	(Fixed)
ASC_e_bike	0.15736	1.625
ASC_e_scooter	−0.86665 **	−6.491
ASC_e_Brommobile	−1.48486 **	−6.917
ASC_e_car	0.53124 **	2.013
Total Travel Cost	−0.01445 **	−2.441
Walking Distance to shared modes	−0.02178	−1.842
In-vehicle Travel Time	−0.03792	−1.820
Model fit		
Initial log-likelihood	−5381.96	
Final log-likelihood	−4707.09	
R2	0.1254	
Adjusted R2	0.1241	
likelihood-ratio test	1349.74	

4.1. Observing heterogeneity in transport mode preferences across classes

Each of the four classes defined in the previous section indicates distinct and significant transport mode preferences. Class 1, with the highest assigned portion of respondents (37.14 %), serves as the largest segment but lacks strong preferences, as indicated by the statistically insignificant ASCs for most modes. The negative valuation of e-scooters (−1.555, t = −1.756) and e-Brommobiles (−3.052, t = −2.297) suggests a general reluctance toward these modes. However, the negative travel cost coefficient (−0.100, t = −2.644) indicates price sensitivity, making this segment price-conscious but leaner towards private (shared) car use.

Class 2, making up 26.79 % of respondents, is highly inclined toward e-bikes, with an ASC of 3.120 (t = 10.314), making it the strongest preference for e-bikes among all classes. However, they do not show a strong preference for e-scooters (0.156, t = 0.349, insignificant) and display an aversion to e-Brommobiles (−2.643, t = −2.197). The ASC for e-cars (1.277, t = 1.468) is positive but not significant, suggesting a mild but uncertain preference. This segment is highly time-sensitive, as seen in the negative coefficients for walking time (−0.152, t = −3.187) and in-vehicle travel time (−0.196, t = −2.199), implying that these travellers favour modes that reduce active and waiting times. Unlike other groups, this class is not cost-sensitive, as reflected in the insignificant travel cost coefficient (−0.022, t = −1.283), suggesting that this

Table 4
Outcomes of Latent Class Model with Increasing Number of Segments.

Number of Classes	No. of parameters	log-likelihood at convergence (LL)	Log-likelihood at 0 (LL(0))	ρ^2	Akaike information criterion (AIC)	Bayesian information criterion (BIC)
1-Class	7	−4707.09	−5381.96	0.1254	9428.18	9470.98
2-Class	15	−3336.99	−5381.96	0.3772	6703.98	6795.7
3-Class	23	−2795.21	−5381.96	0.4806	5644.42	5809.52
4-Class	31	−2223.25	−5381.96	0.5869	4508.51	4698.07
5-Class	39	−2669.3	−5381.96	0.4968	5416.6	5655.08

Table 5
Parameter estimates and model fit of the discrete-choice latent class model.

Latent Class (4 classes)								
Estimated parameters:								31
Iterations:								78
A number of individuals:								418
Total number of observations:								3344
Main effects	**Class 1**		**Class 2**		**Class 3**		**Class 4**	
	Price Sensitive & Private Car Enthusiast **(37%)**		Time-Conscious travellers **(27%)**		Pro-Cycling & Conventional Travelers **(20%)**		Micro-mobility Enthusiasts **(16%)**	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
ASC_bike	fixed to 0	fixed to 0	fixed to 0	fixed to 0	fixed to 0	fixed to 0	fixed to 0	fixed to 0
ASC_e_bike	−0.1363	−0.1983	3.11989	10.3144**	−3.65872	−6.7293**	1.15822	2.4375**
ASC_e_scooter	−1.55536	−1.7564*	0.15552	0.349	−5.48373	−7.1222**	3.13916	6.0307**
ASC_e_Brommobile	−3.05285	−2.2971**	−2.6426	−2.1969**	−5.93053	−4.8499**	2.86716	3.6589**
ASC_e_car	1.66218	1.075	1.27696	1.4682	−4.64114	−3.3917**	2.09814	2.0888**
Total Travel Cost	−0.10016	−2.6442**	−0.02223	−1.2832	−0.06627	−2.4606**	−0.03744	−1.859*
Walking Distance to shared modes	0.02194	0.4025	−0.15202	−3.1875**	−0.0199	−0.2431	−0.08775	−2.739**
In-vehicle Travel Time	−0.0866	−0.846	−0.19612	−2.1986**	−0.23397	−1.9063*	−0.13763	−2.2706**
LL (0, Class)	−5381.96		−5381.96		−5381.96		−5381.96	
LL (final, Class)	−9406.58		−8369.78		−10350.66		−8049.24	
Mean probability	0.3714		0.2679		0.1962		0.1645	
LL (start)	−5381.96							
LL (whole model) at equal shares, LL(0)	−5381.96							
LL (whole model) at observed shares, LL (0)	−4713.38							
LL (final, whole model)	−2223.25							
Rho-squared vs equal shares	0.5869							
Adj.Rho-squared vs equal shares	0.5811							
Rho-squared vs observed shares	0.5283							
Adj.Rho-squared vs observed shares	0.5251							
AIC	4508.51							
BIC	4698.07							

$^{**}p \leq 0.05$, $^{*}p \leq 0.1$.

segment values convenience and efficiency over price.

Class 3, accounting for 19.62 % of individuals, appears to be highly averse to micromobility and small electric modes. A strongly negative ASCs for e-bikes (−3.658, t = −6.729), e-scooters (−5.484, t = −7.122), and e-Brommobiles (−5.930, t = −4.850) indicate a dislike toward these modes. The ASC for e-cars (−4.641, t = −3.392) is also significantly negative, suggesting that this group prefers neither electric cars nor micromobility. This segment is price-sensitive (travel cost: −0.066, t = −2.461) and dislikes additional travel time (in-vehicle time: −0.234, t = −1.906), further reinforcing their preference for conventional transport.

Class 4 represents 16.45 % of respondents and shows relatively strong preferences for micromobility and small electric vehicles. Significant and positive ASCs for e-bikes (1.158, t = 2.437), e-scooters (3.139, t = 6.030), and e-Brommobile (2.867, t = 3.659) indicate some inclination toward electrified light vehicles, over conventional options. The ASC for e-cars (2.098, t = 2.089) suggests a positive inclination toward electric cars as well. However, this class is time- sensitive. The negative impact of walking time (−0.0877, t = −2.739) and in-vehicle travel time (−0.1376, t = −2.270) suggests that this group prioritises speed and convenience. Moreover, the travel cost coefficient (−0.037, t = −1.859) further indicates moderate price sensitivity.

To better define and distinguish the characteristics of respondents within the four classes, we conducted a post-processing analysis of the identified latent classes, focusing on respondents' background characteristics within each class. Initially the respondents in our sample were assigned to one of four latent classes based on the highest posterior probabilities of class membership. After assigning each respondent to one of the four classes, we analysed the demographic characteristics within each class, as presented in Table 6.

Table 7 summarises and compares the respondents' mobility characteristics based on the Latent Class segmentation.

4.1.1. *Price sensitive and private car enthusiast group*

The Price Sensitive and Private Enthusiast Group (37 %) consists mainly of older individuals (60–79 years), with moderate mobility limitations and mixed income levels. They show no strong preference for emerging mobility options and rely heavily on private cars (93 % licensed, 82 % weekly usage). Despite high awareness of shared mobility (85 %), only 9 % have used it. Their trips are mostly social and recreational (59 %), with a preference for the car as the mode of transport due to familiarity and convenience.

4.1.2. *Time-conscious travellers group*

The Time-Conscious Travellers (27 %) favour efficiency and affordability. With a balanced age distribution (50–79 years) and moderate education levels, they prefer e-bikes as an alternative to cars. While 88 % are licensed and 79 % own cars, their weekly car use is lower (66 %). Their trips focus on shopping (23 %) and leisure (63 %), with 21 % using active modes, making e-bikes a key part of their mobility strategy.

4.1.3. *Pro-cycling & conventional travellers group*

This 20 % segment consists of older, well-educated, financially stable individuals (39 % aged 70–79). They are the least reliant on cars (73 % licensed, 67 % ownership, 48 % weekly use) and the most multimodal, with 30 % using public transport and 27 % engaging in active travel. They have the highest experience with shared mobility (29 %) and the longest trips (62 % over 30 min), preferring flexible transport options.

4.1.4. *Micromobility enthusiasts group*

Comprising 16 %, this relatively young senior group are more educated (43 % aged 50–59) and has a progressive approach to transport. Though 85 % have a driver's license, they are less car-dependent (72 % own a car, 72 % weekly use). They show the highest engagement with shared mobility (24 %) and familiarity (90 %). Their travel is split across private cars (69 %), public transport (16 %), and active modes (15 %), with shorter trips favouring micro-mobility solutions.

5. Discussion and recommendations

This study offers important insights into the diverse travel preferences of 50 + age and contributes to research on sustainable mobility in

Table 6
Cross-tabulation of background characteristics of respondents assigned to one of the four latent class.

		Class 1	Class 2	Class 3	Class 4
Variables	**Category**	Price Sensitive & Private Car Enthusiast **(37 %)**	Time-Conscious Travellers **(27 %)**	Pro-Cycling & Conventional Travellers **(20 %)**	Micro-mobility Enthusiast **(16 %)**
Socio-economic					
Age	50–59	28 %	31 %	23 %	43 %
	60–69	38 %	34 %	33 %	38 %
	70–79	28 %	29 %	39 %	19 %
	80≤	6 %	6 %	5 %	0 %
Gender	Male	55 %	52 %	70 %	60 %
	Female	45 %	48 %	30 %	40 %
Education level	Less formally educated	53 %	65 %	35 %	38 %
	Moderately educated (Bachelor's degree)	25 %	16 %	30 %	29 %
	Highly educated (Master's or doctoral degree)	23 %	19 %	34 %	32 %
Income (Total family gross annual)	Less than € 42.400	26 %	36 %	25 %	49 %
	Between € 42.400 and € 71.000	21 %	23 %	29 %	17 %
	Between € 71.000 or more	25 %	19 %	26 %	16 %
	Won't say	28 %	21 %	20 %	18 %
Health ability	I am fully physically mobile	70 %	78 %	80 %	71 %
	My mobility is limited/ I am not a mobile	30 %	22 %	20 %	29 %
Private cars					
License	Yes	93 %	88 %	73 %	85 %
	No	7 %	12 %	27 %	15 %
Having a car	Yes	93 %	79 %	67 %	72 %
	No	7 %	21 %	33 %	28 %
Average use of cars	Weekly	82 %	66 %	48 %	72 %
	Rarely/never	18 %	34 %	52 %	28 %
Shared modes experience variable					
Familiarity with shared mobility concept	Yes	85 %	84 %	80 %	90 %
	No	15 %	16 %	20 %	10 %
Shared modes Experience	Yes	9 %	19 %	29 %	24 %
	No	91 %	81 %	71 %	76 %
Current trip variable					
Main mode	Car as driver and passenger	84 %	64 %	43 %	69 %
	PT(Train/metro/bus/tram)	10 %	15 %	30 %	16 %
	Active modes	6 %	21 %	27 %	15 %
Purpose	To work/study	21 %	14 %	17 %	25 %
	Shopping/ Personal care	19 %	23 %	11 %	25 %
	Social/recreational/visit	59 %	63 %	72 %	50 %
Distance	shorter than 15 min	17 %	17 %	6 %	18 %
	Between 15–30 min	44 %	42 %	32 %	43 %
	longer than 30 min	39 %	42 %	62 %	40 %

Table 7
Comparison of respondents' mobility characteristics based on latent class segmentation.

	Class 1	Class 2	Class 3	Class 4
	Price Sensitive & Private Car Enthusiast	Time-Conscious Travellers	Pro-Cycling & Conventional Travellers	Micro-mobility Enthusiasts
Summary	**(37 %)**	**(27 %)**	**(20 %)**	**(16 %)**
Age distribution	Mostly 60–79	Evenly spread 50–69	Mostly 60–79	Mostly 50–69
Gender	Balanced (55 %M, 45 %F)	Balanced (52 % M, 48 % F)	More males (60 %)	More male (60 %)
Education	Mostly less formally educated (53 %)	At least formally educated (65 %)	Most educated, 34 % highly educated	More educated, 32 % highly educated
Income	Mixed, many undisclosed	Mixed, 36 % below € 42,000	Balanced, 26 % above € 71,000	Lower-income, 49 % below € 42,400
Health ability	70 % fully mobile	78 % fully mobile	80 % fully mobile	71 % fully mobile
Car dependency	Highly car-dependent, 93 % licensed and own a car, 82 % weekly car users	Moderate car use, 88 % licensed, 79 % own a car, 66 % weekly users	Lowest car dependency, 73 % licensed, 67 % own a car, only 48 % weekly users	Less car-dependent, 85 % licensed, 72 % own a car, 72 % weekly car users
Familiarity with shared modes	Low experience (9 %), 85 % aware but not engaged	Moderately aware (84 %), low engagement (19 %)	Highest engagement (29 %), 80 % familiar with shared mobility.	Most aware (90 %), moderate engagement (24 %)
Main mode	Most car-dependent (84 %), least use of alternative modes	Highest active mode use (21 %), driven by e-bike adoption.	Least car-dependent (43 %), most public transport use (30 %)	Still car-dominant (69 %), but highest openness to active transport (15 %)
Purpose	Most social /recreational trips (59 %), least work-related (21 %)	Most shopping trips (23 %), least work-related trips (14 %)	Most social trips (72 %), least shopping trips (11 %)	A most balanced mix of work, shopping, and social trips
Distance	Most long trips (39 % >30 min), least short trips (17 %)	Most balanced mix of short, medium, and long trips.	Most long trips (62 % >30 min), least short trips (6 %).	Most evenly distributed trip durations

aging populations. Using a latent class approach, we identified four distinct traveller profiles with varying degrees of openness to shared mobility options.

Our findings confirm that preferences of older adults for shared mobility are heterogeneous. Some groups are willing to experiment with new, flexible transport modes, while others remain car-dependent due to physical, digital, or psychological barriers. These differences reflect broader challenges in shared mobility adoption among older populations.

By highlighting heterogeneity within the 50 + age group, this study moves beyond simplistic categorizations of "older adults" and supports the development of more inclusive and age-sensitive mobility strategies. Our findings suggest that shared mobility systems—often designed for younger, digitally savvy users—must adapt to accommodate older adults with varying needs and abilities. This has implications not only for service design but also for public engagement, pricing models, and infrastructure planning.

5.1. Policy implications

From a policy perspective, segment-specific interventions are key to promoting shared mobility among ageing populations. Tailoring transport policies to the needs of different traveller groups will support more inclusive urban mobility while reducing private car dependency. Based on the mobility characteristics and preferences of each segment, as identified through the latent class analysis, the following interventions are proposed. Table 8 summarizes practical interventions aligned with each group, including example strategies and implementation notes.

In general, expanding micro-mobility infrastructure, suitable for this age group with considering for safety requirements, integrating e-bikes with public transport, and introducing financial incentives for shared mobility adoption could significantly influence behaviour. Additionally, increasing public awareness and trial opportunities could help hesitant groups familiarize themselves with new mobility options. Implementing these targeted policy interventions can help cities transition toward more inclusive, sustainable, and multimodal transport systems.

These recommendations aim to move beyond one-size-fits-all transport policy. Understanding which groups are more receptive to shared mobility can help policymakers better target investments and communications.

These interventions could be supported through municipal mobility budgets or co-funded by public–private partnerships with shared mobility providers.

5.1. Study limitations

Despite these insights, few limitations should be acknowledged. The study focuses on small to medium-sized cities in the Netherlands, which may limit the generalizability of the findings to larger metropolitan areas or rural regions with different mobility contexts. The online survey

Table 8
Targeted interventions by segment with strategy examples.

Segment	Main Barriers	Suggested Actions	Example Measures
Price Sensitive and Private Car Enthusiast Group	High car reliance, cost sensitivity, habit, low trust in new modes	Lower entry barriersIntoroduce subsidies for mobility optionsImprove accessibilityPromote shared services through trials	Monttly mobility credits (e.g., €10 -15/month for 65+ users) Workshops via senior centres on using mobility apps
Time-Conscious Travelers	Concerned with efficiency, strong preference for quick transport	Expand fast alternatives like e-bikesInvest in e-bike infrastructureIntegrate with public transport	Promote e-bike sharing schemes via pension fonds/pension unions/ communities/local governments (€20/month)e-bike parking at supermarkets and stations
Pro-Cycling & Conventional Travelers Group	Preference for familiar public or active modes	Strengthen walking and cycling networksEnhance integrationSupport multimodal connections	Upgrade bike lanes and lighting
Micro-mobility Enthusiasts Group	Openness to change and interest in innovation, but cost-sensitive	Introduce low-cost micromobility subscriptionsImprove access to shared micro-mobility	Low tariffs (e.g. €1 per scooter ride) during off-peak hoursMicrobility passes bundled with transit subscroptionsExpand micromobility options near transit hubsIncrease public awareness campaigns

format may have also restricted participation among older adults with limited digital literacy. Although efforts were made to ensure demographic diversity through the panel provider, some voices may remain underrepresented. While including demographic characteristics in the latent class model could have enriched the interpretation of class profiles, our attempts to do so led to model instability and non-convergence—likely due to limited variability in the sample, which consisted exclusively of individuals over 50 years old living in relatively homogeneous urban contexts. Lastly, the use of a stated preference method, although valuable for exploring hypothetical behaviour, may not fully capture actual decision-making processes. Future research could complement this work using revealed preference data or experimental interventions.

5.2. Future research

To expand on these findings and address current limitations, future research could diversify the sample to include participants from a broader range of geographic contexts, including both larger urban centres and rural areas. This would enhance the generalizability of the results and may allow for greater demographic diversity in latent class membership estimations. In addition, employing longitudinal methods could provide insight into how travel behaviour evolves over time, particularly in response to aging, policy interventions, or shifts in mobility options. Lastly, evaluating the effectiveness of specific incentive models—such as fare reductions or mobility credits—through real-world pilot programs would provide valuable evidence for designing targeted interventions.

6. Conclusion

This study explores the challenges and opportunities of promoting shared mobility in car-free city centres, with a particular focus on medium-sized Dutch cities and the often-overlooked demographic of middle-aged and older residents. Through the Latent Class Model (LCM), this study captures the diversity of preferences among respondents and provides a nuanced understanding of the factors influencing shared mobility adoption. It identifies latent passenger segments, offering valuable insights for sustainable mobility policies and passenger behaviour analysis.

Findings clearly indicate that older adult travellers (50 +) do not form a very homogeneous group and exhibit some diverse mobility preferences. This underscores the importance of developing targeted, segment-specific transport policies rather than relying on one-size-fits-all approaches. While shared mobility options—such as e-bikes, e-scooters, e-Brommobiel, and e-cars—offer sustainable alternatives, their adoption is hindered by barriers such as perceived inconvenience, lack of reliability, high cost, cleanliness concerns, and limited awareness compared to private cars. For older adults, specific challenges such as unfamiliarity with technology, cognitive decline, and physical limitations further contribute to their hesitancy to engage with shared mobility services.

Segment analysis reveals key behavioural patterns: The Price Sensitive and Undecided Group (37 %) remains highly car-dependent, with little interest in new mobility trends perhaps due to age-related limitations, digital unfamiliarity, and mobility constraints. Time-Conscious travellers (27 %) balance car use with a strong preference for e-bikes, particularly for leisure and shopping trips. Pro-Cycling and Conventional Travelers (20 %) are the least reliant on private cars, embracing a multimodal approach with high public transport and shared mobility engagement. Micromobility Enthusiasts (16 %), though younger and relatively more educated than the rest of the classes, face financial constraints that limit their ability to adopt shared services despite their openness to alternative mobility.

Our findings suggest that policies promoting shared mobility must move beyond age-based assumptions and instead reflect the nuanced travel behaviours, preferences, and constraints of different groups. By doing so, cities can build more inclusive and adaptable transport systems that serve both younger and older generations.

CRediT authorship contribution statement

Fatemeh Torabi Kachousangi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Investigation, Data curation, Conceptualization. **Yashar Araghi:** Writing – review & editing, Validation, Supervision, Software, Methodology, Conceptualization. **Niels van Oort:** Writing – review & editing, Supervision, Conceptualization. **Serge Hoogendoorn:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trip.2025.101592.

Data availability

Data will be made available on request.

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