Journal of Urban Mobility 7 (2025) 100111

Contents lists available at ScienceDirect

Journal of Urban Mobility

journal homepage: www.elsevier.com/locate/urbmob

T2he role of digital mobility skills in the uptake of shared modes at mobility hubs

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A R T I C L E I N F O

Keywords:
Shared mobility
Mobility hubs
Digital skills

A B S T R A C T

The popularity of shared mobility services (such as bike or e-scooter sharing) and mobility hubs is increasing in cities worldwide, with the potential to improve accessibility for all. With the expanding role of shared mobility, travellers must rely on smartphones that are typically needed to use them, and not having the ability to use a smartphone could lead to digital inequality. However, the impact of digital mobility skills on the uptake of shared mobility has hardly been studied. This paper examines the determinants of digital mobility skills and their impacts on the uptake of different forms of shared mobility at mobility hubs. The results of a large-scale survey (N = 2515) across four different cities in Europe were analysed using statistical analyses, showing that lower digital mobility skills are related to other vulnerable-to-exclusion characteristics such as higher age, lower educational level, and unemployment. Furthermore, the uptake of shared modes at mobility hubs is much lower for people with low digital mobility skills, as they face additional barriers to using these services. These results reveal how the growth of app-driven shared mobility services can increase accessibility inequalities.

1. Introduction

Shared mobility services are rising in cities across the globe, with shared micro-mobility schemes present in over 50 % of European cities at the start of 2023 (EIT Urban Mobility, 2023). Furthermore, the development of (shared) mobility hubs is emerging, offering both shared mobility services within walking distance from public transport, as well as other (non-) mobility services, such as places to sit or have a coffee (Geurs et al., 2023). Shared mobility, such as shared bikes or e-mopeds, allows multiple users temporarily access to a mode for a variety of trip purposes (Feigon & Murphy, 2016; Martinez & Keseru, 2023). These shared modes and mobility hubs have the potential to improve mobility for all, and especially for vulnerable groups by, for instance, improving access to transport (De Paepe et al., 2023; Fleming, 2018). In this paper, we aim to analyse the impact of digital mobility skills on the uptake of shared mobility at mobility hubs.

In the literature, several authors have examined individual and mobility-related characteristics that influence the likelihood of using one or multiple shared modes (e.g., Gkavra et al., 2025, Aguilera-Garcia et al., 2020; Efthymiou et al., 2013). Several studies have also highlighted that vulnerable groups, such as females, low-income groups, people with mobility limitations, ethnic minorities, people with lower education, and others (De Paepe et al., 2023; Di Ciommo & Shiftan, 2017; Lucas et al., 2016; McNeil et al., 2018), are more likely to be socially excluded when new developments in transport are not tailored to the needs of these specific groups (Lucas, 2012). Current users of shared modes are generally younger, highly educated and have a higher income, emphasizing that shared modes are, at this moment, not beneficial to all (Fleming, 2018). This underrepresentation of certain groups in the current use of shared modes may indicate lower access to these modes or a lack of ability to use them (Dill & McNeil, 2021).

Vulnerable groups are found to be related to digital inequality in transport services, as characteristics such as age, gender, income and educational level determine digital skills (Durand et al., 2022). However, few studies have operationalised digital skills and examined the role of digital skills in the uptake of shared mobility. Horjus et al. (2022) operationalised digital skills as one of the variables for the intention to use combinations of public transport and shared modes at a tram stop in The Netherlands. This study aims to analyse the impact of digital mobility skills on the uptake of shared mobility at mobility hubs in different cities across Europe. This study operationalises the concept of digital *mobility* skills, identifying the determinants of digital mobility skills and its impacts on shared mobility usage. The paper is based on the results of a large-scale survey conducted in four countries, including:

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https://doi.org/10.1016/j.urbmob.2025.100111
Received 3 November 2024; Received in revised form 5 March 2025; Accepted 6 March 2025
Available online 14 March 2025

Table 1
Overview of the SmartHubs survey sections.

Section	Content	Used in this study
0	Informed consent	Not applicable
1	Socio-demographics, household and digital skills characteristics	Yes
2	Mobility abilities, travel behaviour and mode use	Yes
3	Shared Mobility use, needs and preferences, and intention to use	Yes
4	Mode choice stated preference experiment	No
5	Hub design choice experiment	No
6	Participation in transport	No

Table 2
Classification of digital mobility skills.

Digital mobility skills statements	Level 0	Level 1	Level 2	Level 3
1. Material access				
Respondent owns and uses a mobile phone with internet connection	No	Yes	Yes	Yes
2. Digital skills				
A. Respondent uses an app to plan trips with own vehicle		$\overline{A} \cap \overline{B}$	$A \cup B$	$A \cup B$
B. Respondent uses an app to plan trips with public transport				
C. Respondent uses an app to buy tickets and seat reservations for PT			$\overline{C} \cup \overline{D}$	$C \cap D$
D. Respondent uses an app to transfer money to someone				

Lower Austria and Vienna (Austria), Brussels (Belgium), Munich (Germany) and the metropolitan region of Rotterdam-The Hague (The Netherlands). To the best of our knowledge, this is the first paper to explore the determinants of digital mobility skills, and the first to examine the impact of digital mobility skills on the uptake of shared mobility in different European regions.

This paper is structured as follows. The first section presents a reflection of relevant research that has been reviewed. Then, the methodology of the study is presented, describing the setup of the survey as well as the analysis' methods. Then, results are shared in two sections, one focusing on the determinants of digital mobility skills and one on the impact of those skills on the intention to use shared mobility. This paper finishes with a discussion and conclusion section.

2. Literature review

It is well established that the young, tech-savvy, environmentally conscious individuals are more likely to adopt shared mobility services. Previous research confirms that young, male, highly educated travelers are more likely to adopt bike-sharing (Efthymiou et al., 2013), scooter-sharing (Aguilera-Garcia et al., 2020), e-moped (Aguilera-Garcia et al., 2024), and car-sharing (Prieto et al., 2017; Acheampong and Siiba, 2020; Aguilera-Garcia et al., 2022). In addition, income and dissatisfaction with existing public transit also influence adoption (e.g., Efthymiou et al., 2013, Acheampong & Siiba, 2020). The typical shared mobility users are also "mobility chameleons" since they alternate and combine various shared, private, and public transport modes to accommodate their daily needs (Gkavra et al., 2025).

Contrary to this group, some population groups currently face barriers to using mobility hubs and shared mobility services. In our research, these are referred to as vulnerable groups. High usage costs, lack of information or assistance, and strong dependence on private mobility discourage some individuals from embracing shared mobility systems. Children and teenagers seem more equipped to overcome some existing barriers, such as the more advanced digital skills requirements and have a greater interest in shared mobility. Digitally excluded citizens are less frequent users of public transport and shared modes because of financial resources or not having a smartphone with internet connection, and research shows that smartphone ownership and use increases the likelihood of using multiple modes of transport (Astroza et al., 2017). Digitally excluded citizens often rely on analogue information, printed maps, and information screens to travel autonomously (Geurs et al., 2023).

Shared mobility is currently highly dependent on digital technologies (Martinez & Keseru, 2023), and making a trip with a shared mode is most of the times not possible without using a digital application, requiring users to own a smartphone with an internet connection (Groth, 2019; Jittrapirom et al., 2017). Also, mobility hubs become more digitally integrated, with shared mobility services from various providers integrated into one single application (i.e., Mobility-as-a-Service - MaaS) and users needing to access digital information systems to check timetables or buy tickets (Durand et al., 2022; Geurs et al., 2023). With the expanding role of shared mobility and mobility hubs within transport systems, travellers have to rely on the digital technologies that are needed to use them, and not having the abilities to use them could lead to digital inequality, referring to the unequal access to transport services due to digitalization (Durand et al., 2023a; b; Durand et al., 2022). The digital inequality of vulnerable groups haves an impact on their disadvantaged position in society (De Paepe et al., 2023; Durand et al., 2022; Non et al., 2021; Zhang et al., 2020).

As found by Zhang et al. (2020), owning a smartphone and having knowledge on using it both have impact on the digital inequality of users. These factors relate to the model of Van Dijk, describing the four factors that influence the access to digital technologies: motivation, material access, digital skills and usage (Van Dijk, 2005). Motivation is related to a certain wish and positive attitude toward having digital access and engaging with these technologies (Van Dijk, 2006). Not using digital technologies could be associated to barriers related to a lack of trust, security, and privacy, or with a more general lack of interest (Durand et al., 2022; Groth, 2019). Material access to shared mobility services offered at mobility hubs, is related to physical access to an up-to-date smartphone or digital device with an internet connection (Durand et al., 2022; Van Dijk, 2006). Digital skills are defined as the capacity to use digital resources since access to technology is not the same as being able to benefit from it (Durand et al., 2022; Zhang et al., 2020). Usage of digital technologies is the last step within Van Dijk's model and follows from having enough motivation and sufficient access and skills (Van Dijk, 2006).

Earlier research on digital skills distinguished between medium-related skills, focusing on the skills of operating a digital device, and content-related skills, associated with the ability to process and assess information (Durand et al., 2022; Horjus et al., 2022). Horjus et al. (2022) found that a higher level of digital skills is related to a higher intention to use shared mobility. Digital skills play an important role in multiple assets of shared mobility and mobility hubs, such as using MaaS-applications, requesting a public transport subscription, using ticket machines (Durand et al., 2023a) or digital kiosks (Martinez et al., 2024).

3. Methodology

This section describes the large-scale survey, data collection and data analysis methodology of this study.

3.1. Survey setup

A survey was developed as part of the SmartHubs project with the goal of quantifying the current and potential use of mobility hubs, and the importance of physical and digital integration in hub design (Geurs et al., 2023). The survey consisted of multiple parts, discussed in

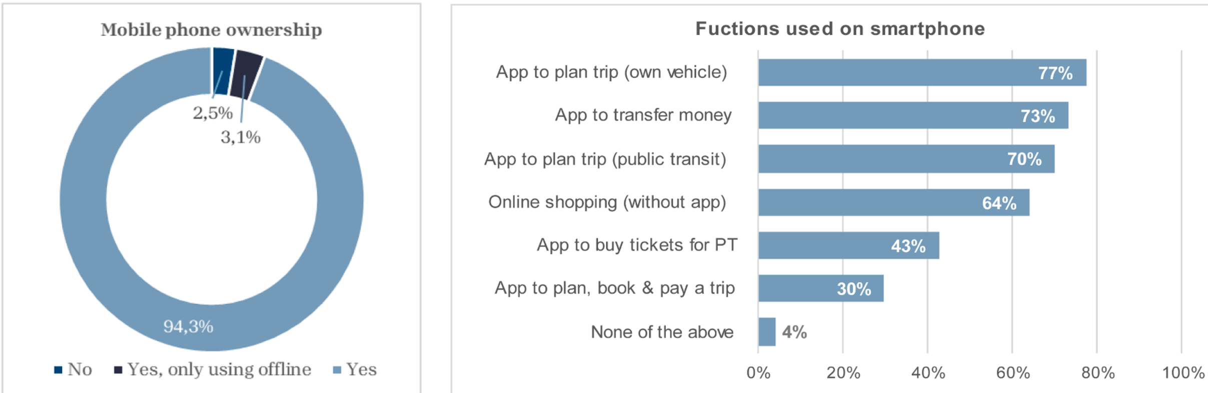

Fig. 1. Mobile phone ownership and phone functions usage amongst the survey respondents.

Table 1, and the questions used for this study focused on the individual characteristics of the personas, and their current and potential travel behaviour regarding shared modes and mobility hubs. All respondents answered the questions corresponding to every section of the survey, with some differences caused by the survey logic (Gkavra et al., 2024). Questions on material access and digital skills are included in survey Section 1 and are described in detail in Section 2.2.

3.2. Digital mobility skills

This paper distinguishes between general digital skills and digital mobility skills. General digital skills are typically defined and operationalised in the literature to describe computer skills, or more generally, the set of skills to use ICT tools and applications (e.g., Van Dijk, 2005; Non et al., 2021). In this paper, we are focussing on digital skills in the mobility domain, in particular the individual's ability to use mobility planning applications and digital mobility services. We developed a digital mobility skills (DMS) scale, combining two of the constructs of Van Dijk's model, namely material access and digital skills (Van Dijk, 2005). The DMS is based on the scale constructed by Horjus et al. (2022). To determine the DMS of a respondent, two survey questions are used, as shown in Table 2: one related to access of a mobile phone with internet connection and the other related to applications used on the respondent's phone (multiple answers were possible). If a person did not own a smartphone, still there were questions about credit card ownership and usage in general (to purchase goods at a store/supermarket, to shop online, to purchase transportation tickets). Our survey did not include different payment methods for shared mobility specifically.

The share of respondents per answer to those questions is shown in Fig. 1. The classification of DMS consist of four levels:

- Level 0 – No digital mobility skills. Respondent does not own or use a mobile phone with internet connection (i.e. smartphone).
- Level 1 – Low digital mobility skills. Respondent uses a smartphone, for calls/ messaging and other offline activities, but not for trip planning applications.
- Level 2 – Medium digital mobility skills. Respondent uses a smartphone and uses trip planning applications (either for their own vehicle or public transport, e.g., Google Maps or public transport planners).
- Level 3 – High digital mobility skills. In addition to level 2, the respondent uses applications to buy tickets or make seat reservations for public transport and uses applications to transfer money.

3.3. Sampling and data collection

The survey targeted both users and non-users of shared mobility and mobility hubs, as well as focusing on particular groups that are vulnerable-to-exclusion when it comes to shared mobility (Martinez & Keseru, 2023). A selection of quotas has been set before the data collection phase, to purposefully recruit sufficient respondents belonging to certain vulnerable groups, based on age, gender, education- and income-level, and digital skills. To accomplish this strategy, a stratified sampling method was chosen to collect respondents in four European areas: Lower Austria and Vienna (Austria), Brussels (Belgium), Munich (Germany) and the metropolitan region of Rotterdam-The Hague (The Netherlands) (Gkavra et al., 2024).

A minimum sample of 500 respondents was targeted for each region, with specific targets based on sociodemographic characteristics of the cities and specific population groups of interest (Table 3). During the time of the data collection, shared mobility providers were operating in all four regions. However, there are variations between the living labs in terms of modal split and specific mode availability. For instance, shared e-scooters are not allowed onto the street within The Netherlands. Nevertheless, the diverse users and non-users from across different European cities offers broad insights into role of digital mobility skills and the determinants of shared mobility usage.

Different recruitment methods were used: (i.) Panel companies (77 % of the final sample), (ii.) Social media (primarily LinkedIn) of project partners and (shared) mobility providers (16 %), and (iii.) Assisted surveys (6 %). The assisted surveys were used for respondents with potentially lower digital skills, who presumably would have difficulties with filling in an online survey, which was filled in during face-to-face meetings in community centres, libraries, and other social gathering

Table 3
Sample requirements as planned for data collection.

	Eastern Austria Region	Brussels Capital Region	City of Munich	Metropolitan Region Rotterdam – The Hague
Sample size		min. 500 respondents per region		
Females		50 %, min. 100 respondents per region		
Older than 65 years	~4 %, min. 100 respondents	~7 %, min. 35 respondents	~12 %, min. 60 respondents	~ 10 %, min. 50 respondents
Low education	~11 %, min. 50 respondents	min. 100 respondents	min. 100 respondents	50 %, min. 200 respondents
Low digital mobility skills	min. 25 respondents per region			
Low-income	20 %, min. 100 respondents	50 %, min. 200 respondents	100 respondents	50 %, min. 200 respondents

Table 4
Predictor variables used in the various analyses.

Predictor variable	Type	Coding	Mean
Gender	Binary	0 = Man / 1 = Female	0.49
Age	Nominal	0 = Below 25 / 1 = 25–34 / 2 = 35–44 / 3 = 45–54 / 4 = 55–64 / 5 = 65–74 / 6 = Above 74	43.15[1]
Educational level	Nominal	0 = Compulsory education or less / 1 = High school graduate / 2 = Senior high school / 3 = University undergraduate degree / 4 = MSc/MA/PhD or equal [Dropped: 5 = Other]	2.27
Income level	Nominal	0 = < €1600 / 1 = €1601-€3200 / 2 = €3201–4800 / 3 = €4801–6400 / 4 = >€6400 / [Dropped: 5 = Do not know or do not want to say]	1.32
Occupation	Nominal	0 = Self-employed / 1 = Employed / 2 = Working in household / 3 = Student / 4 = Unemployed / 5 = Unable to work / 6 = In retirement / [Dropped: 7 = Other]	2.25
Number of years living in the country of residence	Nominal	0 = Born / Not born, but living for: 1 = Over 10 years / 2 = 6–10 years / 3 = 1–5 years / 4 = <1 year / [Dropped: 5 = Prefer not to say]	0.41
Owning a driver's license	Binary	0 = No / 1 = Yes (car and/or motorbike)	0.83
Digital Mobility Skills [2]	Nominal	0 = Level 0 and 1/ 1 = Level 2/ 2 = Level 3	0.81
Use shared modes [2]	Binary	0 = Never / 1 = Yes	0.44
Frequency of walking [2]	Ordinal	0 = Never / 1 = Sometimes / 2 = Often	0.99
Frequency of cycling [2]	Ordinal	0 = Never / 1 = Sometimes / 2 = Often	1.48
Frequency of PT use [2]	Ordinal	0 = Never / 1 = Sometimes / 2 = Often	1.75

Notes: ([1]) Mean is based on the continuous variable of the respondent's age, which is used in the MNL models for the intention to use shared modes.; ([2]) Variables are not used in predicting digital skills, only in predicting the intention to use (Table 8 and Table 9).

places. Data was collected between December 2022 and March 2023, and the survey was available in English, Dutch, French, and German.

Data cleaning consisted of removing respondents that (i.) did not provide their consent to data sharing, (ii.) only opened the starting page of the survey, (iii.) did not have a respondent ID, (iv.) are living outside of the study area, (v.) did not reach the end of the survey or (vi.) had a response duration below four minutes, which was set as the minimum response time. This process resulted in 2515 valid responses, distributed between the living labs of Lower Austria and Vienna (N = 579, 23 %), Brussels (N = 589, 23 %), Munich (N = 542, 22 %) and the metropolitan region of Rotterdam-The Hague (N = 805, 32 %).

3.4. Data analysis

Using the valid responses of the survey, various descriptive statistics are obtained to understand the individual characteristics and travel behaviour of the full sample and the sub-samples of DMS. The current travel behaviour as well as the intention to use shared modes at mobility hubs of the various digital skills levels will be compared against the average frequency of travel.

3.4.1. Digital mobility skills classification

The survey resulted in N = 2515 valid responses after data cleaning. From these, 1111 (44 %) have used one form of shared mobility once in the previous year. Most of these respondents are mobile phone owners (97,5 %) and are using a wide variety of functions of their phones (Fig. 1). While 70 % of the respondents have used an application for public transit trip planning purposes, the share of respondents using apps to plan, book and pay for their trip on a single platform (e.g. MaaS-application) is only 30 %. Based on these questions (Fig. 1 and the classification in Table 2), the respondents could be categorised in the following digital mobility skills categories:

- Level 0 – No digital mobility skills: 5.7 % (N = 143)
- Level 1 – Low digital mobility skills: 12.3 % (N = 309)
- Level 2 – Medium digital mobility skills: 47.9 % (N = 1205)
- Level 3 – High digital mobility skills: 34.1 % (N = 858)

3.4.2. Analysis of determinants of digital mobility skills: CHAID analysis & MNL model

To investigate the determinants of digital mobility skills, a chi-squared interaction detection (CHAID) analysis will be applied. CHAID is a multivariate analysis that identifies homogeneous groups within the dependent variable using a set of predictor variables, by splitting classes based on significant chi-square values (Kass, 1980). While CHAID is a valuable tool for identifying interactions between variables and segmenting data, its application in shared mobility research appears to be limited. Most studies in this field tend to utilize statistical methods such as multinomial logistic regression (e.g. Acheampong and Siiba, 2020, Aguilera-Garcia et al., 2020, Efthymiou et.al. (2013), or other econometric techniques to analyse user behaviour and adoption factors. Nevertheless, this approach was chosen as an exploratory step before regression modelling to identify the most important predictors of digital mobility skills.

For the CHAID analysis, a significance level of 0.05 was used for splitting the nodes of the classification tree. This analysis results in subsets of the data, based on a set of predictor variables that best describe the data (Kass, 1980). The set of potential predictor variables, that will be used as input for the CHAID analysis, is described in Table 4 and is in line with previous research on the relation between socio-demographics and digital skills (e.g., Durand et al., 2022; Non et al., 2021; Zhang et al., 2020). Note that a question was asked how many years the respondent has lived in the country where the survey was conducted, as a proxy for migration background.

The CHAID analysis is performed with a decreased sample size (N = 2056, 82 % of the full sample), as respondents with missing answers to certain questions are dropped from the analysis. The digital mobility skills level 0 and level 1 are merged, to present a larger section of the sample, resulting in the following DMS categories for the dependent variable: (i.) Low digital mobility skills (level 0/1), N = 321 (15.6 %), (ii.) Medium digital mobility skills (level 2), N = 977 (47.5 %) and (iii.) High digital mobility skills (level 3), N = 757 (36.8 %).

In addition to the CHAID analysis, a multinominal logistic regression (MNL) was estimated to compare the results of the CHAID analysis and estimate the degree to which personal characteristics impact the odds of increased digital mobility skills level. Due to the assumption of parallel odds not being met, a MNL model is fitted to the data instead of, for instance, an ordinal model, losing the ordered nature of the DMS categorisation. The MNL model used the same predictor variables as the CHAID analyses (Table 4). People with low digital mobility skills (level 0/1) were taken as the reference category.

3.4.3. Analysis of digital mobility skills' impact on intention to use shared mobility: multinominal logistic regression

Two multinomial logistic regression (MNL) models were estimated to determine the degree to which different personal characteristics and past travel behaviour impact the odds of increased intention to use a shared bike or shared car. The intention to use a shared mode is measured on a 5-point Likert-scale and is re-classified on a 3-point scale: negative, neutral and positive intention. Since these categories have a natural ordering of their classes, an ordinal logistic regression model could have been used. However, when checking for the proportional odds assumption, it was found that the effects of the independent variables were not the same across the three categories of the dependent variable. Therefore, a MNL model was used, and the dependent variable

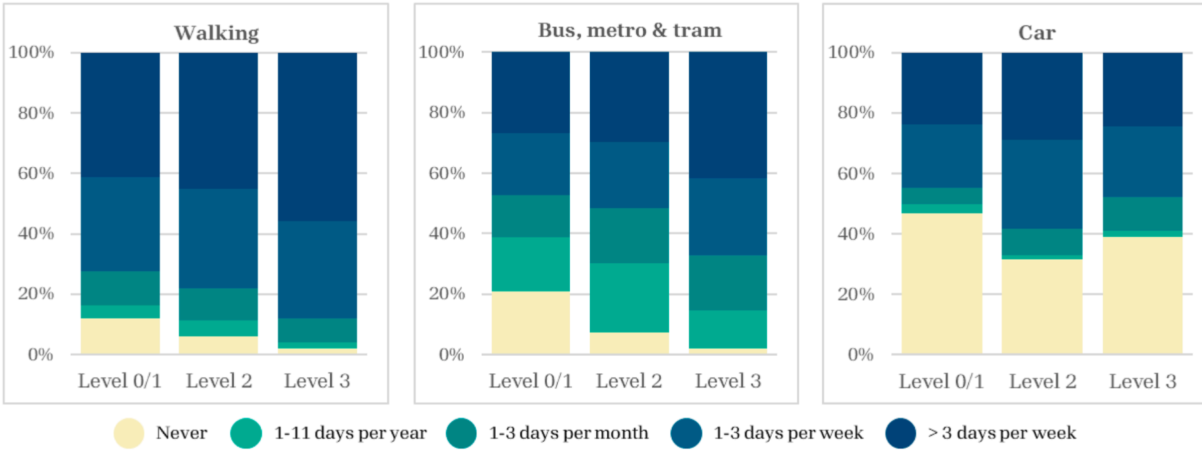

Fig. 2. Frequencies (%) of current mode use for different conventional modes, per DMS category.[11]

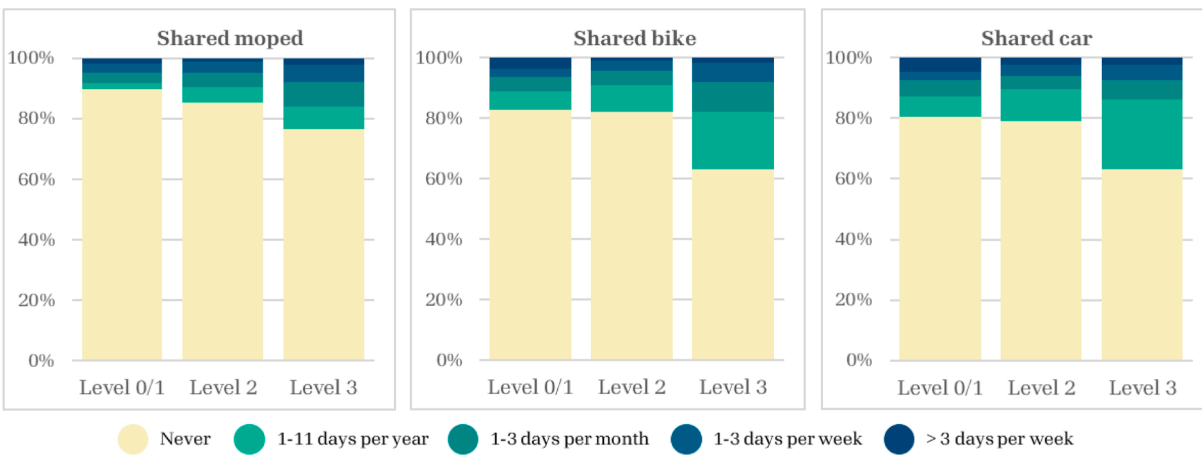

Fig. 3. Frequencies (%) of current mode use for different shared modes, per DMS category.[1]

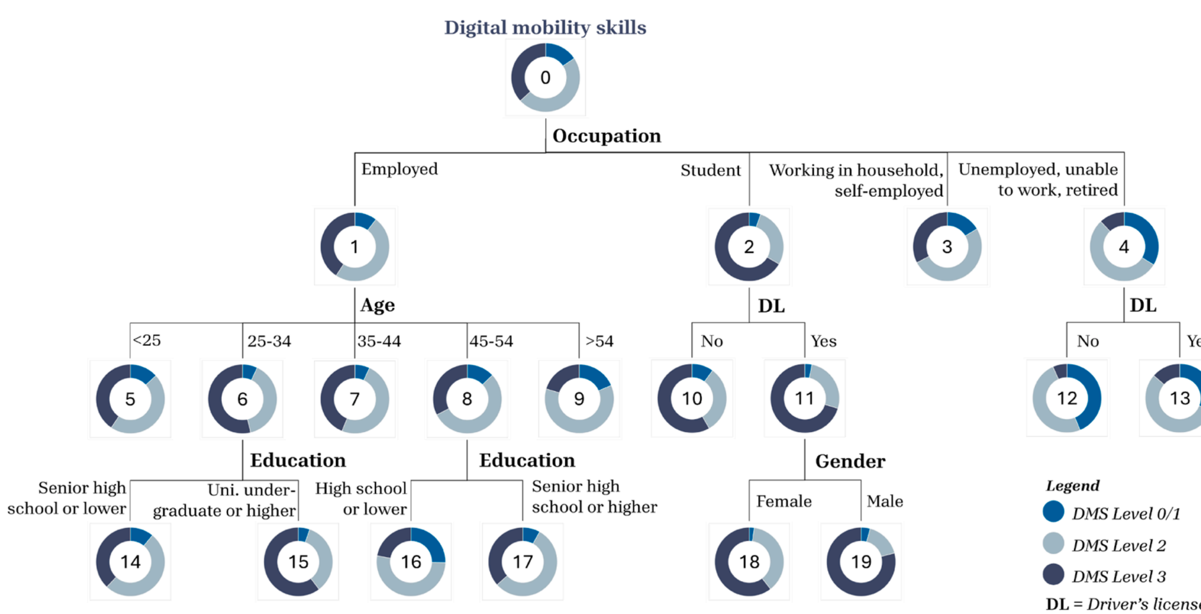

Fig. 4. CHAID classification tree diagram for segmentation of DMS levels.

was treated as a nominal variable. Potential correlations between the independent variables were tested beforehand, and the variable *Frequency of car use* was dropped from the final models due to its high correlation with *Driver's license ownership*. The variables used in the models can be found in Table 4 as well. The final models and model fit information are discussed in Section 4.3 and are shown in Tables 8 and 9.

4. Results

This chapter describes the descriptive statistics of the sample (Section 4.1), the results of the CHAID analysis (Section 4.2) and the multinomial logistic regression models for the intention to use shared modes (Section 4.3).

4.1. Personal characteristics and travel behaviour for different DMS levels

Table 5 (Appendix) gives an overview of the personal characteristics of the full survey sample and cities and the sub-samples for the DMS levels. The differences in each living lab are due to different recruitment methods used to reach respondents (convenient sampling), therefore, to avoid overgeneralisation of the living lab results, we chose to focus on the results of the full sample of users and non-users of shared mobility (hubs).

Based on a z-test, the significance of the difference between the sub-samples is shown in the table as well. Gender is the only characteristic that does not differ significantly between the DMS levels. The proportions of all other variables differ significantly between at least one of the three DMS levels. Respondents with a DMS level 3 are generally younger compared to level 2 and level 0/1. Around 85 % of the DMS level 3 sample is either employed or a student, which is correlated with the relatively high share of low income (<€1600 per month) as well as high income (> €4800 per month). Respondents with low digital mobility skills (level 0/1) are relatively older and have a higher share of people currently retired, unemployed or unable to work, compared to the other levels. The share of respondents with an education level of high school or less is significantly higher for DMS level 0/1 compared to the other levels.

Furthermore, respondents with digital mobility skills level 0/1 are less likely to be born in their current country of residence compared to level 2. However, DMS level 3 shows the highest share of people that are not born in their current country of residence, primarily caused by the relatively high share (13.3 % compared to 7.3 % for the full sample) of people living <5 years in their corresponding country of residence.

The travel behaviour between the three DMS categories is also significantly different. People with no or low digital mobility skills, are less frequent travellers in general. Their walking, biking and public transport use is lower than that of people with medium/high skills. However, respondents with level 2 have a more frequent use of the car, compared to the other levels. Fig. 2 shows the difference in travel frequency for walking, urban public transport and the private car.

Fig. 3 gives a similar overview but for the shared moped, shared bike and shared car. These three modes were available in all living lab locations. Fig. 3 also shows no major difference between shared mode use of level 0/1 and level 2, while level 3 has a significant higher usage level, seemingly caused by the relatively high share of incidental shared bike or shared car trips (1–11 days per year). The shared e-scooter (47 %, excluding the Dutch sample, thus, not shown in Fig. 3) and the shared bike (38 %) are the most used modes for the respondents with DMS level 3. Interestingly, some people with low digital mobility skills are still able to use shared modes. For instance, 17 % of those respondents have used a shared bike during a trip, which could be caused by shared bikes which offer an analogue booking alternative such as the *OV-fiets* (PT-bike) in The Netherlands or *Villo* in Belgium.

4.2. Determinants of digital mobility skills

Results of the CHAID analysis are provided in Fig. 4, showing a classification tree for the digital mobility skills level. The variables are arranged based on their statistical significance in relation to the DMS levels, with the most important predictor variables at the top of the classification tree.

The node numbers in Fig. 4 correspond with the description of the nodes in Table 6. The CHAID classification reveals an underlying structure in the sample when it comes to DMS, and occupation is found to be the most significant variable and is therefore the splitting variable at the first level. Students show the highest percentage of high digital skills, while people in retirement, unemployed or unable to work, have the highest share of DMS level 0/1. Both these groups see the ownership of a driver's license as the following predictor, not owning a driver's license at all increases the probability of a lower digital skills level. The group of people not working and not owning a license (node 12 in Fig. 4) represents the group with the highest share of DMS level 0/1, 43.8 % of respondents are in this group. On the other hand, male students who own a driver's license (node 19) represent the people with the highest share of DMS level 3 (79.2 %). The corresponding female group (node 18) shows the lowest share of DMS level 0/1 (2.3 %).

Amongst currently employed people (node 1), age is a relevant predictor of digital mobility skills. People between the age of 25 and 44 have on average significantly higher DMS levels, while those aged 44 and higher have relatively lower skills. Within certain age categories, the educational level also plays a role as a predictor for digital skills: a higher education level corresponds with a higher DMS.

All in all, the CHAID analysis shows that occupation and age are the most significant classifiers for digital mobility skills, where student and employed respondents have higher skill levels compared to not working individuals. Furthermore, a lower age is related to higher DMS levels. Interesting is that the CHAID model excludes migration background and income level as significant predictors for digital mobility skills. An important note is the accuracy of the CHAID analysis. 55.5 % of the cases are predicted accurately, implying that the other variables that are currently not included might play a role in predicting digital mobility skills.

Additionally, to the CHAID analysis, a MNL model was fitted using the same predictor variables. The MNL model results are presented in Table 7. The results show the parameter estimates for having DMS levels 2 and 3, respectively, compared to the reference category (DMS level 0/1 as a combined category). The model resulted in a McFadden pseudo-R-squared of 0.123, which can be considered a low to moderate model fit. The accuracy of the MNL model has a relatively high margin of error for predicting DMS levels correctly based on the predictor variables, especially for digitally excluded citizens. This could indicate the difficulty of determining digital mobility skills based on socio-demographic characteristics used in this dataset.

When looking into the model outcomes, a similar pattern to the CHAID analysis is found. Generally, gender and current country of residence do not influence the digital mobility skills level. Owning a driver's license, and thus being able to use motorized shared vehicles, increases the odds of having a higher DMS level. Age also shows to be an important predictor, especially when it comes to the difference between level 0/1 and level 3. Current occupation, as was also the case with the CHAID analysis, also has an impact: students and those who are employed have higher odds to have level 3 skills compared to level 0/1. Overall, it can be said that people with a relatively higher age level, who do not own a driver's license and are not employed, have increased odds to have DMS level 0/1. However, the impact of the predictor variables is not the same when comparing level 2 and level 3 with the reference category. People categorised as having DMS level 2 are a more diverse group, whereas there is a more distinct difference between the personal characteristics of those in level 0/1 and level 3.

4.3. Intention to use shared modes at mobility hubs

The potential future use of shared modes at mobility hubs also differs between the DMS categories. Fig. 5 shows the respondents' likelihood of using a shared moped, bike or car at a mobility hub during a future trip. In general, respondents are most likely to use a shared e-bike at a mobility hub, approximately 22 % is positive ('likely' or 'very likely'), while the shared cargo bike is lowest on the ranking, with 15 % of respondents stating it is (very) likely that they will use the vehicle during a future trip at a mobility hub. However, this potential use of shared modes is not equally divided between the digital skills segments: the higher the DMS level, the higher the potential use of shared modes. For instance, approximately 11 % of respondents level 0/1 is positive about potentially using a shared bike at a mobility hub in the future, while 33 % of respondents level 3 is. The shares of neutrals do not differ significantly between the DMS levels for most modes. with an exception for the shared e-bike.

Fig. 6 presents the ratio between respondents with a positive likelihood of using the mode at a mobility hub and those who have a negative likelihood. As all values are below one, every shared mode has more respondents with a negative intention than with a positive one. People with low DMS have the highest ratio for every of the six modes. A similar pattern is visible for all DMS categories when it comes to the popularity of the different shared modes. The e-bike and e-scooter are most popular amongst the respondents, while the shared moped and cargo bike are the overall least popular modes.

The model results for the two MNL models are in Table 8 (regarding the intention to use a shared bike use) and Table 9 (shared car). Both models show a good model fit when it comes to their final loglikelihood statistics ($\chi^2 = 563.694$ and 494.473, $p < 0.001$). and show a decent model fit with a Nagelkerke R-squared of 0.24 and 0.22, respectively. Both models use a negative intention to use the shared modes as their reference category for the dependent variable.

The model for potential shared bike use shows that age, occupation, the previous use of shared modes and the frequency of walking have an effect across both categories. Higher age corresponds with a lower intention to use a shared bike, and people who are currently employed also have an increased intention. People who already have experience with using any shared mode are more likely to use shared bikes in the future. When people do not have any experience, the odds of having a positive intention decrease with a factor 3.4. The role of the shared bike in a combined trip with public transport is also undescribed by the model results, showing that less frequent use of PT decreases the odds of wanting to use a shared bike. The model for shared bikes also reveals that digital mobility skills have a significant effect between the negative and positive intended use. People with DMS level 0/1 and level 2 are less likely to use shared bikes in the future, compared to level 3.

The shared car model (Table 9) has multiple effects in common with the shared bike model. Age, previous use of shared modes and the frequency of PT use show similar relationships. People who have a higher age and less experience with shared mode use in the past are less likely to use shared cars in the future. The same holds for public transport use: model results show that less frequent use of PT decreases the odds of using a shared car. Here, it is important to note that the question stated the likelihood of using shared cars at mobility hubs, which could explain the relationship with public transportation use. What is different between the bike and car models, is the significance of owning a driver's license, which increases the likelihood of wanting to use a shared car in the future. The impact of DMS is like that of the shared bike model, showing how people with lower digital skills are less inclined to use a shared car during their future trips.

5. Discussion & conclusions

In this paper, we examined the determinants of digital mobility skills (DMS) and combine these findings by determining the impact of digital mobility skills on the uptake of different forms of shared mobility at mobility hubs.

Our study provides new insights into the determinants and concept of digital mobility skills and uses the concept of DMS as an explicit variable to determine the intention to use different shared modes. To the best of our knowledge, this is the first paper to explore the determinants of digital mobility skills. In our study, we also expand and generalize the research Horjus et al. (2022), who used digital skills as one of the variables for the intention to use different modes at a case study location in The Netherlands. Our study makes use of data from a large scale, multi country survey, focusing on a wide selection of shared modes, and making them comparable. We show that shared modes at mobility hubs, although they have the potential to increase accessibility for all (De Paepe et al., 2023), still do not benefit everyone and does not reach their full potential.

Digital mobility skills are clearly shown to impact the intention to use shared modes. The results from the large-scale survey across four cities (N = 2515), show that both the current use of shared modes, as

Table 6
Results of CHAID analysis per node of the classification tree.

Node	Level 0/1		Level 2		Level 3		Primary independent variables		
(level)	*n*	%	*n*	%	*n*	%	*Variable*	*Sig.*	*Split values*
0	321	15,6	977	47,5	757	36,8			
1 (1)	121	10,4	566	48,8	474	40,8	Occupation	<0.001	Employed
2 (1)	14	5,4	73	28,0	174	66,7	Occupation	<0.001	Student
3 (1)	26	16,4	81	50,9	52	32,7	Occupation	<0.001	Working in household or Self-employed
4 (1)	160	33,8	257	54,2	57	12,0	Occupation	<0.001	Unemployed, Unable to work, or In retirement
5 (2)	14	13,2	49	46,2	43	40,6	Age	<0.001	< 25
6 (2)	24	7,0	134	39,2	184	53,8	Age	<0.001	25 - 34
7 (2)	22	6,9	156	49,2	139	43,8	Age	<0.001	35 - 44
8 (2)	29	12,9	122	54,5	73	32,6	Age	<0.001	45 - 54
9 (2)	32	18,6	105	61,0	35	20,3	Age	<0.001	> 54
10 (2)	8	10,1	25	31,6	46	58,2	Driver's license	0.019	No
11 (2)	6	3,3	48	26,4	128	70,3	Driver's license	0.019	Yes
12 (2)	46	43,8	52	49,5	7	6,7	Driver's license	0.005	No
13 (2)	114	30,9	205	55,6	50	13,6	Driver's license	0.005	Yes
14 (3)	11	11,0	51	51,0	38	38,0	Education level	0.001	Compulsory education; High school graduate; Senior high school
15 (3)	13	5,4	83	34,3	146	60,3	Education level	0.001	University under-graduate; MSc/MA/PhD or equal degree
16 (3)	16	25,4	33	52,4	14	22,2	Education level	0.004	Compulsory education; High school graduate;
17 (3)	13	8,1	89	55,3	59	36,6	Education level	0.004	Senior high school; University under-graduate; MSc/MA/PhD or equal degree
18 (3)	2	2,3	32	37,2	52	60,5	Gender	0.033	Female
19 (3)	4	4,2	16	16,7	76	79,2	Gender	0.033	Male

Table 7
MNL model results for determining digital mobility skills.

Variables	*Digital mobility skills level = 2*					*Digital mobility skills level = 3*				
	B	Wald	Exp(B)	CI LB [a]	CI UB [a]	B	Wald	Exp(B)	CI LB [a]	CI UB [a]
Intercept	−0.893	1.369				**−1.745***	**4.085**			
Gender										
Male	−0.117	0.713	0.890	0.678	1.167	0.110	0.524	1.117	0.828	1.505
Female	0[b]					0[b]				
Age										
Below 25	0.538	1.330	1.713	0.686	4.276	**2.151****	**8.979**	**8.593**	**2.104**	**35.090**
25–34	0.800	3.526	2.225	0.966	5.129	**2.616*****	**14.333**	**13.675**	**3.531**	**52.969**
35–44	**0.993***	**5.517**	**2.700**	**1.179**	**6.187**	**2.439*****	**12.498**	**11.457**	**2.964**	**44.283**
45–54	0.548	1.781	1.729	0.774	3.864	**1.785****	**6.802**	**5.960**	**1.558**	**22.800**
55–64	0.383	1.040	1.466	0.703	3.059	0.977	2.143	2.655	0.718	9.814
65–74	0.185	0.390	1.204	0.673	2.154	0.823	1.965	2.277	0.721	7.192
Above 74	0[b]					0[b]				
Education level										
Compulsory edu.	−0.412	2.603	0.662	0.401	1.093	**−0.842****	**8.450**	**0.431**	**0.244**	**0.760**
High school grad.	**−0.507***	**4.139**	**0.602**	**0.369**	**0.982**	**−0.727****	**7.004**	**0.484**	**0.282**	**0.828**
Senior high school	−0.129	0.316	0.879	0.560	1.379	−0.476	3.778	0.621	0.384	1.004
Uni. undergraduate	−0.040	0.027	0.961	0.593	1.557	0.092	0.133	1.096	0.669	1.795
MSc/MA/PhD	0[b]					0[b]				
Income level										
Below €1601.-	0.320	0.625	1.376	0.623	3.040	−0.501	1.561	0.606	0.276	1.330
€1601.- - €3200.-	0.604	2.418	1.830	0.854	3.921	−0.130	0.118	0.878	0.418	1.845
€3201.- - €4800.-	**0.892***	**4.881**	**2.440**	**1.106**	**5.384**	0.158	0.160	1.172	0.539	2.549
€4801.- - €6400.-	0.677	2.388	1.968	0.834	4.647	0.457	1.138	1.579	0.682	3.654
More than €6400.-	0[b]					0[b]				
Occupation										
Self-employed	0.156	0.170	1.168	0.557	2.449	0.521	1.193	1.684	.661	4.290
Employed	0.484	2.616	1.623	0.902	2.920	**0.945***	**5.281**	**2.574**	**1.149**	**5.765**
Work in household	0.535	1.172	1.707	0.649	4.492	1.074	3.129	2.926	.891	9.614
Student	**1.133***	**5.547**	**3.106**	**1.210**	**7.977**	**2.404*****	**18.911**	**11.072**	**3.746**	**32.725**
Unemployed	−0.053	0.020	0.948	0.457	1.969	−0.426	0.655	0.653	.233	1.831
Unable to work	−0.455	1.222	0.635	0.284	1.421	−0.185	0.106	0.831	.273	2.531
In retirement	0[b]					0[b]				
Years living in Country of Res.										
Born	1.069	3.165	2.912	0.897	9.455	0.470	0.726	1.599	0.543	4.712
living >10years	0.820	1.730	2.271	0.669	7.706	0.175	0.090	1.191	0.379	3.749
living 6–10 y.	0.364	0.250	1.438	0.346	5.987	−0.095	0.019	0.909	0.237	3.488
living 1–5 y.	0.579	0.733	1.784	0.474	6.717	0.418	0.453	1.519	0.450	5.130
living <1 year	0[b]					0[b]				
Driver's license										
No	**−0.510****	**9.151**	**.601**	**0.432**	**0.836**	**−0.720*****	**13.429**	**0.487**	**0.331**	**0.715**
Yes	0[b]					0[b]				

Notes: *** $p < 0.001$. ** $p < 0.01$. * $p < 0.05$; ([a]) CI = Confidence Interval. LB = Lower Bound. UB = Upper Bound; ([b]) Reference category. **Model information**: N = 2056; McFadden Pseudo $R^2 = 0.123$; Likelihood ratio test $\chi^2 = 509.86$ ($p < 0.001$).

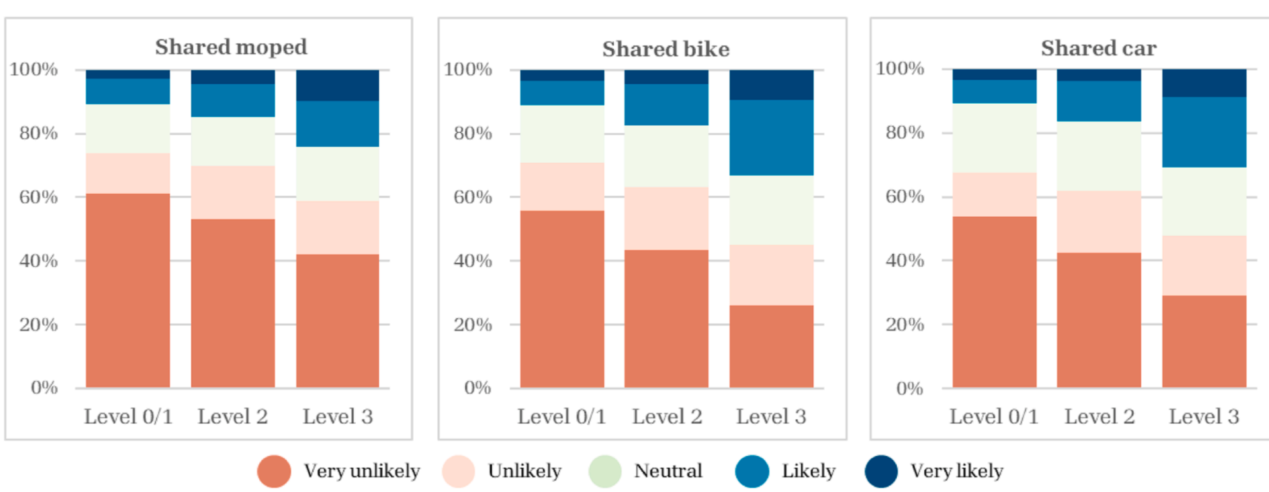

Fig. 5. Likelihood of using differing shared modes at a mobility hub in the future, per DMS category.

well as the intention to do so in the future, are higher for those with high digital mobility skills. While urban mobility systems become increasingly dependent on shared modes and the digital booking applications associated with them, people with lower digital mobility skills could experience a decrease in their accessibility (Durand et al., 2023a). With this digitalisation trend also happening in the development of mobility

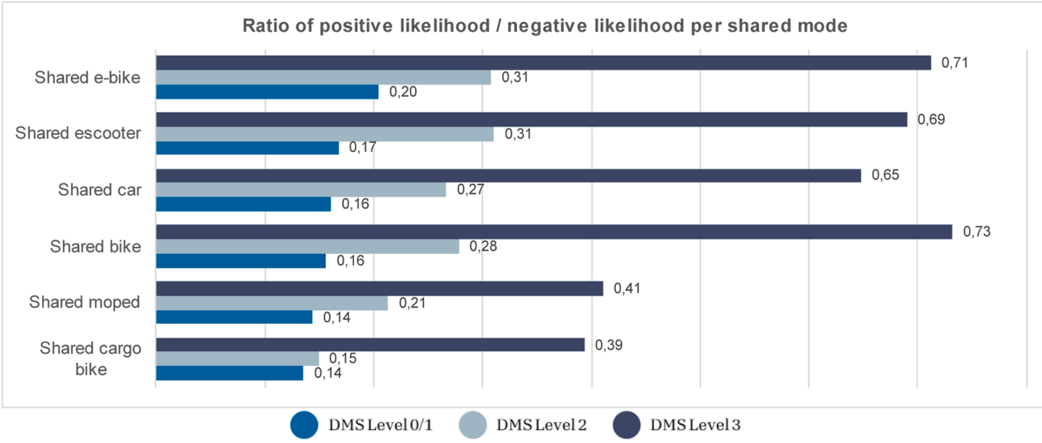

Fig. 6. Ratio positive/negative likelihood per shared mode, per DMS category.

Table 8
MNL model results for shared bike use intention.

Variables	*Intention to use shared bike = neutral*					*Intention to use shared bike = positive*				
	B	Wald	Exp(B)	CI LB [a]	CI UB [a]	B	Wald	Exp(B)	CI LB [a]	CI UB [a]
Intercept	−0.199	0.215				0.814	2.874			
Age	**−0.022*****	**15.678**	**0.979**	**0.968**	**0.989**	**−0.022*****	**15.024**	**0.978**	**0.967**	**0.989**
Gender										
Male	0.175	2.372	1.191	0.954	1.487	0.005	0.002	1.005	0.800	1.263
Female	0[b]					0[b]				
Occupation										
Self-employed	0.238	0.517	1.269	0.663	2.427	0.583	2.428	1.791	0.861	3.726
Employed	**0.504***	**4.254**	**1.655**	**1.025**	**2.671**	**0.688***	**4.881**	**1.990**	**1.081**	**3.663**
Work in household	**1.022****	**8.351**	**2.780**	**1.390**	**5.561**	0.345	0.443	1.411	0.511	3.894
Student	0.288	0.754	1.333	0.697	2.553	0.584	2.334	1.793	0.848	3.790
Unemployed	0.402	1.434	1.496	0.774	2.890	**1.121****	**8.834**	**3.067**	**1.465**	**6.421**
Unable to work	0.192	0.220	1.212	0.543	2.706	0.734	2.236	2.083	0.796	5.450
In retirement	0[b]					0[b]				
Education level										
Compulsory edu.	0.134	0.413	1.143	0.760	1.719	−0.368	2.718	0.692	0.447	1.072
High school grad.	0.019	0.009	1.019	0.686	1.515	**−0.592****	**7.391**	**0.553**	**0.361**	**0.848**
Senior high school	−0.025	0.021	0.975	0.694	1.370	−0.237	2.063	0.789	0.571	1.090
Uni. undergraduate	0.262	2.363	1.300	0.930	1.817	−0.188	1.338	0.829	0.602	1.140
MSc/MA/PhD	0[b]					0[b]				
Driver's license										
No	−0.062	0.162	0.940	0.695	1.271	−0.147	0.806	0.863	0.626	1.190
Yes	0[b]					0[b]				
DMS level										
Level 0/1	0.103	0.315	1.108	0.774	1.586	**−0.624****	**8.750**	**0.536**	**0.354**	**0.810**
Level 2	−0.001	0.000	0.999	0.775	1.289	**−0.343****	**7.222**	**0.709**	**0.552**	**0.911**
Level 3	0[b]					0[b]				
Used shared mode										
Never	**−0.561*****	**20.500**	**0.570**	**0.447**	**0.727**	**−1.334*****	**103.56**	**0.263**	**0.204**	**0.341**
Yes	0[b]					0[b]				
Freq. of walking										
Never	**−0.744***	**5.782**	**0.475**	**0.259**	**0.872**	**−1.227****	**7.392**	**0.293**	**0.121**	**0.710**
Sometimes	−0.183	1.190	0.833	0.599	1.157	−0.338	3.320	0.713	0.496	1.026
Often	0[b]					0[b]				
Freq. of bike use										
Never	−0.088	0.402	0.916	0.698	1.202	−0.191	1.809	0.826	0.625	1.092
Sometimes	−0.033	0.055	0.967	0.732	1.278	**−0.310***	**4.464**	**0.734**	**0.551**	**0.978**
Often	0[b]					0[b]				
Freq. of PT use										
Never	−0.164	0.474	0.848	0.531	1.355	**−0.725***	**4.302**	**0.484**	**0.244**	**0.961**
Sometimes	−0.181	1.991	0.835	0.649	1.073	**−0.317***	**5.772**	**0.728**	**0.563**	**0.943**
Often	0[b]					0[b]				

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; ([a]) CI = Confidence Interval. LB = Lower Bound. UB = Upper Bound; ([b]) Reference category. **Model information**: N = 2407; Nagelkerke Pseudo $R^2 = 0.244$; Likelihood ratio test $\chi^2 = 563.694$ ($p < 0.001$).

hubs, the risk emerges that mobility hubs are not designed for all (Durand et al., 2022). While Horjus et al. (2022) did not find a correlation between shared transport and public transit use, our results show that lower public transport use is related to a lower intention of using a shared bike or car. This strengthens the risk for exclusion, as digitally excluded citizens are already less frequent public transport users (Astroza et al., 2017).

Digital mobility skills are related to certain personal characteristics.

Table 9
MNL model results for shared car use intention.

Variables	*Intention to use shared car = neutral*					*Intention to use shared car = positive*				
	B	Wald	Exp(B)	CI LB [a]	CI UB [a]	B	Wald	Exp(B)	CI LB [a]	CI UB [a]
Intercept	−0.162	0.157				0.054	0.015			
Age	**−0.018*****	**10.851**	**0.982**	**0.972**	**0.993**	0.000	0.000	1.000	0.989	1.011
Gender										
Male	−0.005	0.002	0.995	0.804	1.232	0.121	1.067	1.129	0.897	1.420
Female	0[b]					0[b]				
Occupation										
Self-employed	0.175	0.340	1.191	0.662	2.144	0.372	1.219	1.450	0.750	2.804
Employed	0.125	0.313	1.133	0.732	1.752	**0.544***	**4.312**	**1.723**	**1.031**	**2.878**
Work in household	0.246	0.496	1.278	0.646	2.532	−0.365	0.448	0.694	0.238	2.024
Student	0.117	0.141	1.124	0.611	2.066	0.293	0.696	1.340	0.674	2.665
Unemployed	0.456	2.238	1.577	0.868	2.866	0.697	3.781	2.009	0.994	4.057
Unable to work	−0.022	0.003	0.979	0.467	2.050	0.698	2.519	2.009	0.849	4.757
In retirement	0[b]					0[b]				
Education level										
Compulsory edu.	**0.467***	**5.098**	**1.595**	**1.064**	**2.393**	0.332	2.434	1.394	0.918	2.116
High school grad.	0.386	3.829	1.471	0.999	2.166	−0.193	0.816	0.824	0.542	1.254
Senior high school	0.289	2.911	1.336	0.958	1.863	−0.141	0.696	0.868	0.623	1.210
Uni. undergraduate	0.245	2.043	1.277	0.913	1.787	−0.222	1.803	0.801	0.579	1.108
MSc/MA/PhD	0[b]					0[b]				
Driver's license										
No	**−0.972*****	**36.140**	**0.378**	**0.276**	**0.519**	**−1.200*****	**40.035**	**0.301**	**0.208**	**0.437**
Yes	0[b]					0[b]				
DMS level										
Level 0/1	0.191	1.182	1.211	0.858	1.709	**−0.740*****	**12.293**	**0.477**	**0.315**	**0.721**
Level 2	0.011	0.007	1.011	0.787	1.299	**−0.471*****	**13.138**	**0.625**	**0.484**	**0.806**
Level 3	0[b]					0[b]				
Used shared mode										
Never	**−0.564*****	**21.336**	**0.569**	**0.448**	**0.723**	**−1.603*****	**134.79**	**0.201**	**0.154**	**0.264**
Yes	0[b]					0[b]				
Freq. of walking										
Never	**−0.855****	**8.018**	**0.425**	**0.235**	**0.769**	−0.017	0.003	0.984	0.532	1.818
Sometimes	0.058	0.141	1.060	0.781	1.439	−0.026	0.021	0.974	0.682	1.391
Often	0[b]					0[b]				
Freq. of bike use										
Never	0.191	2.018	1.211	0.930	1.576	0.060	0.175	1.062	0.801	1.409
Sometimes	0.165	1.416	1.179	0.899	1.547	−0.254	2.910	0.775	0.579	1.039
Often	0[b]					0[b]				
Freq. of PT use										
Never	−0.012	0.003	0.988	0.642	1.519	**−0.872****	**7.235**	**0.418**	**0.222**	**0.789**
Sometimes	−0.190	2.353	0.827	0.649	1.054	**−0.449*****	**11.625**	**0.638**	**0.493**	**0.826**
Often	0[b]					0[b]				

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; ([a]) CI = Confidence Interval. LB = Lower Bound. UB = Upper Bound; ([b]) Reference category. **Model information**: N = 2407; Nagelkerke Pseudo $R^2 = 0.217$; Likelihood ratio test $\chi^2 = 494.473$ ($p < 0.001$).

Low digital mobility skills are primarily correlated with other vulnerable-to-exclusion characteristics, such as being unemployed or unable to work, having a higher age, or having a lower educational level. The personal characteristics found using the CHAID analysis, and confirmed by the MNL models, correspond with previous studies, which reported that age, gender, income and educational levels are connected to digital inequalities (e.g.. De Paepe et al., 2023; Durand et al., 2022). However, digital mobility skills cannot be fully predicted using the seven personal characteristics that are used in this research. The previously discussed results show that people with either low or high digital mobility skills, while having common characteristics, are not a homogeneous group. This is an important finding, as it suggests that digital mobility skills are not easily recognizable and could imply that other factors may play a role, such literacy and numeracy, as suggested in the literature on general digital skills (Non et al., 2021). These variables were not measured in the survey and could therefore not be added to the analysis.

The large effect that digital mobility skills and previous shared mode experience have on the intention to use those modes in the future, showcases the importance of lowering these modes' digital barriers. These two variables also strengthen each other: low digital skills are related to lower use of shared mode usages in daily trips, which also decreases the likelihood of using these types of shared vehicles in the future, increasing the divide between experienced users and non-users. Our results show that the intention to use is, both for the full sample as for respondents with level 0/1 digital mobility skills, highest for the shared e-bike and e-scooter. Additionally, these modes do not require a driver's license, which is an important determinant of DMS. Focussing on the digital accessibility of these micro-mobility modes, which are broadly available throughout Europe, should therefore be priority from both shared mobility and public transport providers, as it could increase public transport use overall (Horjus et al., 2022).

This paper has limitations related to the convenient sampling and respondent recruitment strategy of the survey. The sample of respondents is not representative of the population in the four metropolitan regions included in this study. Future research is needed to examine the role of digital mobility skills in more representative survey samples. In particular, a metric, such as the DMS categorisation used in this paper, would be useful to add to national representative travel surveys, allowing a comprehensive examination of the role of digital skills in travel behaviour patterns and the uptake of shared mobility.

Our findings have policy and governance implications. Here, we briefly discuss a few directions as the questions what measures need to be taken to lower digital barriers, and how they are to be implemented is beyond the scope of this paper. In line with Durand et al. (2023b), who examined digital inequality in public transport, we think there is no one-size-fits-all solution to develop a more inclusive shared mobility system in the digital era, but various complementary measures can be taken. A first group of possible measures relate to the accessible design of digital products and services from the start by involving various groups of potential users. For shared mobility to have an impact, digital apps must be easier to use (e.g. in line with universal design principles) and/or citizens need to be offered training and/or analogue solutions. Only then will people with lower digital mobility skills get the motivation and courage to engage with those new forms of mobility. A second group of measures relates to communication and education. Communicating clearly in accessible language is relevant for any type of mobility services. In particular, knowledge of and information on the mobility services at mobility hubs is a major barrier for those who are vulnerable-to-excluded (Garritsen et al. 2024; Martinez et al., 2022). Education and training are furthermore relevant. More attention is needed to, for exclusion, on-site assistance and digital training to encourage and help first-time users (Martinez et al., 2024), to increase the overall ease of using those modes. As the intention to use is higher with more experience, this could potentially increase their digital mobility skills and knowledge of shared mobility hubs and shared modes, which has a positive effect on making shared modes a more inclusive offer of transport. Also, the role of the public transport staff should not be underestimated as they are the interface between the system and the user.

Monitoring of digital skills is also relevant. The low predictability of digital mobility skills as found in this paper, indicates that these skills need to be measured specifically in mobility studies. Having material access to a mobile phone, with potential access to shared mobility applications, is not enough to measure digital mobility skills, as stated by Zhang et al. (2020) or Van Dijk (2005). This calls for the inclusion of digital skills variables in user studies and standard travel surveys conducted to understand usage and non-usage of shared mobility and mobility hubs. In addition, inclusion of these variables in panel studies, such as The Netherlands Mobility Panel (Hoogendoorn-Lanser et al., 2015) would allow monitoring the development of digital skills and the use of shared modes over time. However, nowadays travel and panel surveys are mostly web-based, and monitoring digital skills of low digitally skilled people will require investment in mixed-method recruitment of respondents which comes with additional costs.

Moreover, a major unsettled question is how measures to develop more inclusive digital shared mobility services as described above can be implemented. Shared mobility services are primarily company-owned services, which are unlikely to allocate or have (sufficient) budget to properly address issues around digital inequality. The business models of shared mobility systems are oriented towards financial and economic efficiency. Achieving changes to improve inclusion in shared mobility will require different governance models, including direct financial support (e. g. through subsidies) and/or permits and concessions for shared mobility service operators which include incentives and/or requirements regarding standards for the provision of non-digital services. Adding digital equity requirements to shared mobility permit requirements is an important way forward. A review of over 200 shared micromobility services across the U.S. reveals that over 60 % of programmes have equity-oriented policy requirements set by cities and transportation agencies to reduce access disparities. Over one third included requirements to have smartphone alternatives, cash payment compatibility and over 25 % included requirements for multilingual services (Brown & Howell, 2024). However, more research is needed on what requirements deliver equitable outcomes. Brown and Howell (2024) state that key challenge to evaluate outcomes is data availability, as typically cities have evaluation requirements to collect data on start and end points of trips, but no data is collected on user characteristics. Moreover, tackling systemic issues that underlie digital barriers like poverty and low literacy is crucially relevant, but goes beyond what shared mobility providers can do.

Funding statement

This study was conducted as part of the project 'Smart Mobility Hubs as Game Changers in Transport', supported by JPI Urban Europe EN-UAC. project number 99950070, and NWO Grant 438-21-431 supporting the contribution from the University of Twente.

CRediT authorship contribution statement

Kelt É. Garritsen: Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anna B. Grigolon:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Karst T. Geurs:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Acknowledgements

The authors thank the SmartHubs teams from the University of Natural Resources and Life Sciences (Vienna), Technical University of Munich and the Vrije Universiteit Brussel for their contribution to the SmartHubs survey and data-gathering process and thank all participants for their contribution to the survey.

Appendix

Table 5
Descriptive statistics of the full sample datasets and DMS sub-samples.

Variable	Sample size		DMS Level 0/1 [2]		DMS Level 2 [2]		DMS Level 3 [2]	
Full sample	N = *2515*	*100 %*	N = *452*	*18 %*	N = *1205*	*48 %*	N = *858*	*34 %*
Austria	N = *579*	*23 %*	N = *74*	*13 %*	N = *309*	*53 %*	N = *196*	*34 %*
Brussels	N = *589*	*23 %*	N = *174*	*30 %*	N = *264*	*45 %*	N = *151*	*26 %*
Munich	N = *542*	*22 %*	N = *64*	*12 %*	N = *196*	*36 %*	N = *282*	*52 %*
MRDH (NL)	N = *805*	*32 %*	N = *140*	*17 %*	N = *436*	*54 %*	N = *229*	*28 %*
Gender								
Female	N = 1278	50.8 %	N = 228	50.4 %	N = 636	52.8 %	N = 414	48.3 %
Male	N = 1228	48.8 %	N = 221	48.9 %	N = 566	47.0 %	N = 441	51.4 %
Other / Prefer not to say	N = 9	0.4 %	N = 3	0.6 %	N = 3	0.3 %	N = 3	0.3 %
Age category								

(*continued on next page*)

Table 5 (*continued*)

Variable	Sample size		DMS Level 0/1 [2]		DMS Level 2 [2]		DMS Level 3 [2]	
18–24 years	N = 390	15.5 %	N = 51 [a]	11.3 %	N = 141 [a]	11.7 %	N = 198 [b]	23.1 %
25–34 years	N = 563	22.4 %	N = 59 [a]	13.1 %	N = 220 [b]	18.3 %	N = 284 [c]	33.1 %
35–44 years	N = 450	17.9 %	N = 47 [a]	10.4 %	N = 229 [b]	19.0 %	N = 174 [b]	20.3 %
45–54 years	N = 380	15.1 %	N = 71	15.7 %	N = 197	16.3 %	N = 112	13.1 %
55–64 years	N = 339	13.5 %	N = 92 [a]	20.4 %	N = 196 [a]	16.3 %	N = 51 [b]	5.9 %
65–74 years	N = 307	12.2 %	N = 99 [a]	21.9 %	N = 174 [b]	14.4 %	N = 34 [c]	4.0 %
> 75 years	N = 85	3.4 %	N = 32 [a]	7.1 %	N = 48 [b]	4.0 %	N = 5 [c]	0.6 %
Not answered	N = 1	0.0 %	N = 1	0.2 %	N = 0	0.0 %	N = 0	0.0 %
Household income-level								
< €1600 per month	N = 535	21.3 %	N = 120 [a]	26.5 %	N = 225 [b]	18.7 %	N = 190 [a, b]	22.1 %
€1600, €4800 per month	N = 1261	50.1 %	N = 195 [a]	43.1 %	N = 653 [b]	54.2 %	N = 413 [a]	48.1 %
> €4800 per month	N = 330	13.1 %	N = 33 [a]	7.3 %	N = 127 [a]	10.5 %	N = 170 [b]	19.8 %
Don't know/prefer not to say	N = 389	15.5 %	N = 104 [a]	23.0 %	N = 200 [b]	16.6 %	N = 85 [c]	9.9 %
Education level								
Compulsory education or less	N = 322	12.8 %	N = 89 [a]	19.7 %	N = 174 [b]	14.4 %	N = 59 [c]	6.9 %
High school graduate	N = 371	14.8 %	N = 100 [a]	22.1 %	N = 186 [b]	15.4 %	N = 85 [c]	9.9 %
Senior high school	N = 686	27.3 %	N = 125 [a, b]	27.7 %	N = 364 [b]	30.2 %	N = 197 [a]	23.0 %
University undergraduate	N = 615	24.5 %	N = 70 [a]	15.5 %	N = 252 [b]	20.9 %	N = 293 [c]	34.1 %
MSc/MA/PhD or equal	N = 460	18.3 %	N = 47 [a]	10.4 %	N = 200 [b]	16.6 %	N = 213 [c]	24.8 %
Other	N = 61	2.4 %	N = 21 [a]	4.6 %	N = 29 [a, b]	2.4 %	N = 11 [b]	1.3 %
Country of Residence								
Born in CoR [1]	N = 1957	77.8 %	N = 337 [a]	74.6 %	N = 990 [b]	82.2 %	N = 630 [a]	73.4 %
Living in CoR for > 5 years	N = 351	14.0 %	N = 78	17.3 %	N = 163	13.5 %	N = 110	12.8 %
Living in CoR for < 5 years	N = 183	7.3 %	N = 22 [a]	4.9 %	N = 47 [a]	3.9 %	N = 114 [b]	13.3 %
Prefer not to say	N = 24	1.0 %	N = 15 [a]	3.3 %	N = 5 [b]	0.4 %	N = 4 [b]	0.5 %
Occupation								
Self-employed	N = 132	5.2 %	N = 26	5.8 %	N = 63	5.2 %	N = 43	5.0 %
Employed	N = 1328	52.8 %	N = 151 [a]	33.4 %	N = 663 [b]	55.0 %	N = 514 [b]	59.9 %
Working in household/unpaid Student	N = 76	3.0 %	N = 22 [a]	4.9 %	N = 36 [a, b]	3.0 %	N = 18 [b]	2.1 %
Unemployed	N = 353	14.0 %	N = 34 [a]	7.5 %	N = 102 [a]	8.5 %	N = 217 [b]	25.3 %
Unable to work	N = 15	4.9 %	N = 41 [a]	9.1 %	N = 68 [b]	5.6 %	N = 15 [c]	1.7 %
In retirement	N = 74	2.9 %	N = 32 [a]	7.1 %	N = 31 [b]	2.6 %	N = 11 [b]	1.3 %
Other	N = 411	16.3 %	N = 140 [a]	31.0 %	N = 234 [b]	19.4 %	N = 37 [c]	4.3 %
	N = 17	0.7 %	N = 6	1.3 %	N = 8	0.7 %	N = 3	0.3 %
Physical problem walking								
Yes	N = 301	12.0 %	N = 111 [a]	24.6 %	N = 144 [b]	12.0 %	N = 46 [c]	5.4 %
No	N = 2214	88.0 %	N = 341 [a]	75.4 %	N = 1061 [b]	88.0 %	N = 812 [c]	94.6 %

Notes: ([1]) CoR = Country of (current) residence. ([2]) A z-test with adjusted p-values was used to compare column proportions of DMS to explore if there is a significant difference between the columns at a 0.05 significance level. Similar letters in superscript, ([a]), ([b]) or ([c]), denote columns whose proportions do not differ significantly. If there are no letters at all, there is no significant proportional difference between any of the DMS categories (e.g., for gender, there is no significant difference between any of the DMS categories).

References

Acheampong, R. A., & Siiba, A. (2020). Modelling the determinants of car-sharing adoption intentions among young adults: The role of attitude, perceived benefits, travel expectations and sociodemographic factors. *Transportation, 47*(5), 2557–2580. https://doi.org/10.1007/s11116-019-10029-3

Aguilera-García, Á., Gomez, J., Baeza, M.Á., Rangel, T., & Vassallo, J. M. (2024). Which factors influence the use of shared and privately-owned e-scooters in the city of Madrid? Implications for urban mobility. *Cities (London, England), 147*, Article 104785. https://doi.org/10.1016/j.cities.2023.104785

Aguilera-García, Á., Gomez, J., & Sobrino, N. (2020). Exploring the adoption of moped scooter-sharing systems in Spanish urban areas. *Cities (London, England), 96*, Article 102424. https://doi.org/10.1016/j.cities.2019.102424

Aguilera-García, Á., Gomez, J., Antoniou, C., & Vassallo, J. M. (2022). Behavioral factors impacting adoption and frequency of use of carsharing: A tale of two European cities. *Transport Policy, 123*, 55–72. https://doi.org/10.1016/j.tranpol.2022.04.007

Astroza, S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Lavieri, P. S., & Dias, F. F. (2017). Analysis of the impact of technology use on multimodality and activity travel characteristics. *Transportation Research Record: Journal of the Transportation Research Board, 2666*, 19–28. https://doi.org/10.3141/2666-03

Brown, A., & Howell, A. (2024). Mobility for the people: Equity requirements in US shared micromobility programs. *Journal of Cycling and Micromobility Research*, (2), 1–10. https://doi.org/10.1016/j.jcmr.2024.100020

De Paepe, L., Van Acker, V., & Witlox, F. (2023). To share or not to share. By whom is the question. Acceptability and acceptance of shared transport services by vulnerable groups. *Transport Reviews, 43*(5), 935–969. https://doi.org/10.1080/01441647.2023.2185314

Di Ciommo, F., & Shiftan, Y. (2017). Transport equity analysis. *Transport Reviews, 37*(2), 139–151. https://doi.org/10.1080/01441647.2017.1278647

Dill, J., & McNeil, N. (2021). Are shared vehicles shared by all? A review of equity and vehicle sharing. *Journal of Planning Literature, 36*(1), 5–30. https://doi.org/10.1177/0885412220966732

Durand, A., Zijlstra, T., van Oort, N., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2022). Access denied? Digital inequality in transport services. *Transport Reviews, 42*(1), 32–57. https://doi.org/10.1080/01441647.2021.1923584

Durand, A., Zijlstra, T., Hamersma, M., Hoen, A.t., van Oort, N., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2023a). Who can I ask for help?": Mechanisms behind digital inequality in public transport. *Cities (London, England), 137*, Article 104335. https://doi.org/10.1016/j.cities.2023.104335

Durand, A., Zijlstra, T., Hamersma, M., t Hoen, A., van Oort, N., Hoogendoorn, S., & Hoogendoorn-Lanser, S. (2023b). Fostering an inclusive public transport system in the digital era: An interdisciplinary approach. *Transportation Research Interdisciplinary Perspectives, 22*, Article 100968.

Efthymiou, D., Antoniou, C., & Waddell, P. (2013). Factors affecting the adoption of vehicle sharing systems by young drivers. *Transport Policy, 29*(C), 64–75.

EIT Urban Mobility (2023). The progress of shared micro mobility across Europe | Keynote by Augustin Friedel. https://marketplace.eiturbanmobility.eu/insights/the-progress-of-shared-micro-mobility-across-europe.

Feigon S., & Murphy C. (2016). Shared Mobility and the Transformation of Public Transit. The National Academies Press.

Fleming, K. L (2018). Social equity considerations in the new age of transportation: Electric. Automated. And shared mobility. *Journal of Science Policy and Goverance, 13* (1).

Garritsen, K. E., Grigolon, A. B., & Geurs, K. T.. Deliverable D5.3 SmartHubs Equity Assessment. https://www.smartmobilityhubs.eu/_files/ugd/c54b12_ad08aedca18246e0be9f7f0d65cbf6f8.pdf.

Geurs, K., Grigolon, A., Münzel, K., Gkiotsalitis, K., Duran-Rodas, D., Büttner, B., … Klementschitz, R. (2023). The Smarthubs integration ladder: A conceptual model for the categorisation of shared mobility hubs. *Transport Reviews, 44*(1), 112–139. https://doi.org/10.1080/01441647.2023.2239499

Gkavra, R., Roider, O. Susilo, Y.O. (2024). SmartHubs Deliverable D5.1 Mobility hubs impacts on mobility patterns and behavioural change. https://www.smartmobilityhubs.eu/_files/ugd/c54b12_34adbea6988f477aa01feaf7d0f0d182.pdf.

Gkavra, R., Susilo, Y. O., Grigolon, A., Geurs, K., & Roider, O. (2025). Mobility chameleons: The current and potential users of shared micromobility. *Travel behaviour and society, 39*. https://doi.org/10.1016/j.tbs.2024.100967. Article 100967. Advance online publication.

Groth, S. (2019). Multimodal divide: Reproduction of transport poverty in smart mobility trends. *Transportation Research Part A: Policy and Practice., 125*, 56–71. https://doi.org/10.1016/j.tra.2019.04.018

Hoogendoorn-Lanser, S., Schaap, N. T. W., & Olde Kalter, M. J. (2015). The Netherlands Mobility Panel: An innovative design approach for web-based longitudinal travel data collection. *Transportation Research Procedia, 11*, 311–329. doi.org/10.1016/j.trpro.2015.12.027.

Horjus, J. S., Gkiotsalitis, K., Nijënstein, S., & Geurs, K. T (2022). Integration of shared transport at a public transport stop: Mode choice intentions of different user segments at a mobility hub. *Journal of Urban Mobility, 2*, Article 100026. https://doi.org/10.1016/j.urbmob.2022.100026

Jittrapirom, P., Caiati, V., Feneri, A., Ebrahimigharehbaghi, S., Alonso-González, M. J., & Narayan, J. (2017). Mobility as a service: A critical review of definitions. *Assessments of Schemes. and Key Challenges. Urban Planning., 2*(2), 13–35. https://doi.org/10.17645/up.v2i2.931

Kass, G. V (1980). An exploratory technique for investigating large quantities of categorical data. *Journal of the Royal Statistical Society. Series C (Applied Statistics)., 29*(2), 119–127. https://doi.org/10.2307/2986296

Lucas, K. (2012). Transport and social exclusion: Where are we now?. In *Transport Policy, 20* pp. 105–113). https://doi.org/10.1016/j.tranpol.2012.01.013

Lucas, K., Moore, J., Bates, J., & Carrasco, J. A (2016). Modelling the relationship between travel behaviour and social disadvantage. *Transportation Research Part A, 85*, 157–273. https://doi.org/10.1016/j.tra.2016.01.008

Martinez, L., & Keseru, I. (2023). Digital shared mobility services: Operationalizing the capabilities approach to appraise inclusivity. In I. Keseru, & A. Randhahn (Eds.), *Towards user-centric transport in europe 3: Making digital mobility inclusive and accessible* (pp. 59–73). Springer International Publishing. https://doi.org/10.1007/978-3-031-26155-8_4.

Martinez L., Pappers J., & Keserü I. (2022). SmartHubs Deliverable D3.2 needs of users and digitally excluded citizens. https://www.smartmobilityhubs.eu/_files/ugd/c54b12_e1c66f737c2a46ef85f64edb5f60f8d1.pdf.

Martinez, L., Garritsen, K., Baguet, J., Grigolon, A., Münzel, K., Keserü, I., & Geurs, K. (2024). Digital kiosks and inclusivity: A novel perspective on mobility hubs. *European Transport Research Review, 16*(1), 53. https://doi.org/10.1186/s12544-024-00676-8

McNeil, N., Broach, J., & J, D. (2018). *Breaking Barriers to Bike Share: Lessons on Bike Share Equity*. Institute of Transportation Engineers.

Non M., Dinkova M., & Dahmen B. (2021). Skill up or get left behind? Digital skills and labor market outcomes in The Netherlands. https://www.cpb.nl/sites/default/files/omnidownload/CPB-Discussion-Paper-419-Skill-up-or-get-left-behind-Digital-skill-labor-market-outcomes-netherlands.pdf.

Prieto, M., Baltas, G., & Stan, V. (2017). Car sharing adoption intention in urban areas: What are the key sociodemographic drivers? *Transportation Research Part A, 101*, 218–227.

Van Dijk. J.A.G.M. (2005). The deepening divide. Inequality in the Information society. Sage. https://doi.org/10.4135/9781452229812.

Van Dijk, J. A. G. M. (2006). Digital divide research. Achievements and shortcomings. *Poetics (Hague, Netherlands), 34*(4), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004

Zhang, M., Zhao, P., & Qiao, S. (2020). Smartness-induced transport inequality: Privacy concern. Lacking knowledge of smartphone use and unequal access to transport information. *Transport Policy, 99*, 175–185. https://doi.org/10.1016/j.tranpol.2020.08.016