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DOI:
10.1016/j.tbs.2022.09.004

Travel Behaviour and Society 30 (2023) 178–191

Contents lists available at ScienceDirect

Travel Behaviour and Society

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

Something for every one? - An investigation of people's intention to use different types of shared electric vehicle

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ARTICLE INFO

Keywords:
Consumer adoption
Electric mobility
Mobility hubs
Shared mobility
Regression

ABSTRACT

Whereas most shared mobility providers offer one type of shared electric or conventional vehicle, electric mobility hubs, or eHUBs, offer users access to a range of modes in publicly accessible locations. An apparent strength of eHUBs lies in their appeal to different user groups that may have vastly different mobility needs. However, to date, there is little evidence to support this claim. Consequently, based on a questionnaire sampling>2,500 potential eHUB users across five European countries, several of the factors that may influence the likely adoption of eHUBs were investigated using a multiple linear regression approach. In particular, factors such as respondents' demographic characteristics, travel behaviour, and attitudes based on Diffusion of Innovation Theory and the Theory of Planned Behaviour, were considered as predictors of the intention to use either shared e-bikes, e-cargobikes, e-cars, and/or e-scooters. This analysis revealed that the intention to use different types of vehicles is indeed predicted by different combinations of factors, with holding a positive attitude towards shared mobility emerging as the strongest predictor across the board. Beyond attitudes, younger respondents, as well as regular cyclists and public transport users, expressed a greater interest in using all modes, except e-cars. Finally, current car drivers positively anticipate using shared electric cars. Taken together, our results suggest that the different shared electric modes offered by an eHUB may indeed appeal to different audiences, strengthening the case for shared mobility providers to diversify their fleets. However, the potential to replace trips by private car appears limited.

1. Introduction

Shared electric mobility hubs, also called eHUBs, allow users to access a range of shared electric vehicles on an on-demand basis from designated public hub locations. In contrast to free-floating sharing schemes, where shared vehicles can be accessed and left within a specified zone, eHUBs follow a station-based scheme, where shared vehicles are rented from one hub and then returned to either the same or a different a hub. The difference between eHUBs and more traditional shared vehicle schemes is that the latter are often limited to one mode of travel (e.g., only e-bikes or e-cars), whereas eHUBs aim to offer access to more than one shared electric vehicle type to potential users – that is, any combination of *at least two* different shared modes (e.g., e-bikes and e-cars, e-cargobikes and e-scooters, or e-bikes, e-cars, and e-scooters, etc.) – thus serving more varied mobility needs. These may involve, for instance, intermodal combinations, such as arriving at the mobility hub by e-bike or e-scooter sharing and then continuing the trip in a shared electric car.

Shared electric vehicles at the hub may either be provided by one or several shared mobility providers, carrying implications for the ease of use of the mobility services (e.g., using a single app and registration process for multiple suppliers rather than having to access several apps and register with each supplier individually). In the eHUBS project, for instance, shared electric vehicles are provided by different shared mobility providers working in close collaboration with partner cities. Instead of shared electric vehicles, conventional shared cars or bicycles could also be offered at mobility hubs, albeit the focus of eHUBs is on shared electric mobility because electric cars have zero tailpipe emissions and thus *may* be more sustainable compared to internal combustion engine (ICE) vehicles (Manjunath & Gross, 2017). E-bikes, on the other hand, enable users to cover greater distances with less effort compared to regular bicycles (Fishman & Cherry, 2016), despite potential disbenefits in terms of health and emissions due to replacing conventional bicycles (Hoj et al., 2018; Van Cauwenberg et al., 2019).

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https://doi.org/10.1016/j.tbs.2022.09.004
Received 4 July 2021; Received in revised form 18 September 2022; Accepted 20 September 2022
Available online 29 September 2022

The added value of providing more than one shared (electric) vehicle type (by the same or different providers) has been questioned, however. Claasen (2020), for instance, suggests that the added value of mobility hubs over common carsharing schemes is limited, despite acknowledging the utility of non-car travel modes for various day-to-day situations and reduced travel costs. However, as the evidence surrounding the incremental value of multimodal mobility hubs versus monomodal shared mobility schemes is still fairly limited, the authors analysed people's intentions to use different shared electric modes from eHUBs.

With regard to the latter, a major assumption underlying the present work is that *if* the different shared electric vehicle types offered by eHUBs appeal to different audiences (e.g., different age groups, genders, or mode users), then this suggests that there may be added value of more diverse shared electric vehicle fleets provided via e-mobility hubs. On the other hand, if respondents unanimously show favouritism towards any particular mode (e.g., shared e-cars), then this would suggest that there may be little added value of eHUBs versus common monomodal shared mobility services (e.g., see Claasen, 2020). Hence, the principal research question of the current study can be summarised as follow:

RQ: Do different types of shared electric vehicles appeal to different target groups, therefore providing initial support for the added value of eHUBS over monomodal sharing schemes?

With the aim to address this research question, a one-to-one comparison of common predictors of people's intention to use four different shared electric modes available via eHUBs is offered. To this end, responses from a sample of 2,540 survey respondents across seven cities in five European countries including Amsterdam (NL), Arnhem (NL), Nijmegen (NL), Dreux (FR), Kempten (GER), Leuven (BE), and Manchester (UK), were examined. By revealing differences in the intention to use diverse shared electric vehicle types, the potential added value of shared mobility hubs also can be explored. Yet, it should be noted that the current approach is not primarily concerned with the emission reduction potential of eHUBs. While, in the best-case scenario, people will relinquish their private car in favour of shared mobility options, there is always the possibility of shared modes replacing trips already being made using sustainable modes, such as by walking, cycling, or public transport. While acknowledging this possibility, here, the authors are less concerned with what travel modes shared (light) electric vehicles may replace. Instead, the authors aim to advance research on the potential added value of shared mobility hubs, whose purpose is to accommodate different user groups and trip purposes. This will subsequently aid local authorities and policy makers to make future decisions with regard to shared mobility provision.

2. Literature review

Recent literature on people's intention to adopt shared mobility services is briefly reviewed (see Table 1). In general, previous literature tends to consider the intention to adopt single shared mobility modes,

Table 1
Overview of recent literature predicting the usage of shared mobility services/modes.

Study	Mode	Study context/participants	Method	Predictors / Relevant findings
Mattia et al. (2019)	Free-floating carsharing	Car sharing users in Italy (Rome, Milan, Turin, etc.)	Structural equation modelling (SEM)	Attitude, perceived behavioural control, and subjective norm have a significant influence on the future intention to re-use free-floating car sharing.
Li & Kamargianni (2020)	Shared Mobility Services	Chinese commuters	Integrated choice and latent variable model	The probability to choose bike-sharing could be positively affected by "willingness to be a green traveller" and "satisfaction with cycling environment," and car-sharing choice is positively correlated with "advocacy of car-sharing service."
Garaus and Garaus (2021)	Shared Mobility services	Online panel, resident in pre-selected German cities	Online experiment	Environmental claims can stimulate perceived ecological benefits, which, in turn, positively affect carsharing usage intention.
Ko et al. (2021)	Shared Mobility services	Citizens living in Gyeonggi Province, Korea	Logistic regression analysis	Gender, car ownership, and education, among variables reflecting socio-demographic characteristics, have significant effects on intention to use shared mobility.
Jie et al. (2021)	Shared Mobility Services	Survey of residents in the shire of Wanneroo, AUS	EFA, binary logistic regression	Women are larger users of shared mobility except for bike sharing; Higher income groups were more likely to use shared mobility options.
Yu et al. (2018)	Bike-sharing	Online + Offline survey of Chinese students and workers	PLS-SEM	The intention to use commercial bike-sharing systems is positively affected by perceived usefulness of the system, attitude toward bike-sharing, and perceived behavioural control.
Nikiforiadis et al. (2019)	Bike-sharing	Users of the bike-sharing system of the city of Thessaloniki, Greece	Classification tree and binary logit model	Younger ages and those who are not currently users are those most likely to be attracted to the system. Other factors, such as car usage frequency, education, and income also appeared to have slight impact on travellers' intention to use the system more often.
Gao et al. (2019)	Bike-sharing	Chinese residents	SEM	Perceived usefulness, facilitating conditions and perceived risks were important determinants to the adoption of bike sharing systems.
Ge et al. (2020)	Bike-sharing	Beijing, China	Multiple linear regression and SEM	Social support, personal preference, and attitude toward bikesharing positively predicted the intention to use bikesharing. Young people were more willing to use bikesharing services.
Li et al. (2021)	Bike-sharing	Small-sized Chinese city	SEM	Attitude, subjective norm, and perceived behavioural control have direct positive effects on the intention to use shared electric bicycles. Environmental concern and policy support have indirect positive effects.
Becker & Rudolf (2018)	Cargobike-sharing	Free cargobike-sharing users in Germany and Austria	Descriptive statistics	Results show that 46 percent of respondents maintain that they would have made the trip by car in the absence of a cargo-bike-sharing operator, indicating the high potential of cargo-bikesharing to reduce car usage.
Dorner & Berger (2020)	Cargobike-sharing	Bicycle-savvy persons in Austria	Correlation analysis	Men, well-educated people, and cyclists are particularly interested in cargobikes and cargobike-sharing.
Eccarius & Lu (2020)	E-scooter	Taiwanese university students	PLS-SEM	Awareness-knowledge about the sharing system and environmental values influence the formation of usage intention in indirect ways.
Kopplin et al. (2021)	E-scooter	German public transportation service users	PLS-SEM	Environmental concerns and individual convenience (i.e., performance expectancy) emerge as the main drivers for using e-scooter.
Mitra & Hess (2021)	E-scooter	Residents in Toronto and surrounding municipalities	Weighted logistic regression models	Preference toward trip efficiency, and environment and health-consciousness, were positively associated with potential e-scooter consideration.

such as bike-, scooter- or carsharing (e.g., Akgün-Tanbay et al., 2022; Campisi et al., 2021; Eccarius & Lu, 2020; Gao et al., 2019; Mattia et al., 2019), whereas fewer publications focus on shared mobility services in a broader sense (e.g., Jie et al., 2021; Ko et al., 2021; Reck & Axhausen, 2021). Our research aligns itself with the latter stream of research, focusing specifically on the intention to adopt different shared electric vehicle types available via eHUBs. Hereby, a major novelty of our approach lies in the simultaneous consideration of the availability of four distinct shared modes including e-bikes, e-cargobikes, e-scooters, and/or e-cars.

From the literature, various approaches to investigating shared mobility use and intentions can be identified. First, theoretical approaches aim to predict the intention to use shared mobility services directly via statistical models. In most cases, these studies rely on commonly used theoretical frameworks, such as the Theory of Planned Behaviour (e.g., Li et al., 2021; Mattia et al., 2019; Yu et al., 2018). Second, interest in shared mobility services or bundles is explored via Stated Preference surveys (e.g., Asgari et al., 2018; Ho et al., 2020). Third, the characteristics of existing users of shared mobility services are examined (e.g., Jie et al., 2021; Reck & Axhausen, 2021). Each approach delivers valuable insights into who uses, or intends to use, various shared mobility options, although findings have been shown to vary across different studies and geographical regions, as well as shared mobility modes.

According to Reck and Axhausen (2021), for instance, 'shared micromobility users [in Zurich] tend to be young, university-educated males in full-time employment living in affluent households without children or cars'. Similarly, Ko et al. (2021) find a greater willingness to use shared mobility among men rather than women, although the authors could not determine age as a significant factor for the intention to use shared mobility services. In contrast, Jie et al. (2021) report that in the shire of Wanneroo, Australia, women are greater users of shared mobility. All of the aforementioned studies suggest, however, that people from higher income groups and those with a higher education background are more likely to use shared mobility options, suggesting a significant gap in shared mobility provision. Apart from people's demographic characteristics, it has been found that TPB constructs (i.e., attitude, perceived behaviour control, and subjective norms; Li et al., 2021; Mattia et al., 2019; Yu et al., 2018), as well as environmental concerns (Eccarius & Lu, 2020; Garaus and Garaus, 2021; Kopplin et al., 2021; Li & Kamargianni, 2020), are among the key predictors of the intention to use shared mobility services.

In the present study, the influence of a combination of attitudinal, demographic and travel related factors on the intention to use four different types of shared electric vehicles is considered. The main novelty in this study lies in the simultaneous consideration of several shared electric vehicle types, allowing for a side-by-side comparison of the factors that predict the intention to use each mode. By examining each travel mode in turn, it can be determined whether different shared vehicle types do or do not appeal to different target audiences. The four shared electric vehicles and their characteristics are listed below:

- **Shared e-cars**. According to estimations by Ciari and Becker (2017), car sharing could more than half the number of cars on the road if applied at a large scale, including urban and rural areas (Wappelhorst et al., 2014), leading to lasting environmental benefits in the form of improved air quality (Migliore et al., 2020). As might be expected, existing car sharing users tend to express greater interest in electric car sharing, which may also help raise the acceptance of EVs (Schlüter & Weyer, 2019). Furthermore, EV sharing has also been shown to increase the willingness to reduce private car use or forego the purchase of a private car (Firnkorn & Müller, 2015).
- **Shared e-bikes**. In contrast to conventional bicycles, e-bikes can maintain speed with less effort (Fishman & Cherry, 2016) and thus are a particularly attractive alternative to older adults who want to travel greater distances (Van Cauwenberg et al., 2019). Yet, the competitive advantage of e-bikes compared to private cars decreases with travel distance (Ciari & Becker, 2017) and health benefits of cycling may be reduced (Hoj et al., 2018). Moreover, it has been shown that (shared) e-bikes not only substitute trips by private car, but may also substitute trips by public transport or conventional bicycle (Bieliński et al., 2021; Kroesen, 2017). It is commonly found that younger age groups tend to express a greater interest in bike sharing services and use them more frequently (Ge et al., 2020; Nikiforiadis et al., 2019), while perceived usefulness is one of the key predictors of adoption (Gao et al., 2019; Yu et al., 2018).
- **Shared e-cargobikes**. Due to their carrying capacity, cargobikes have been shown to be particularly effective in substituting car trips. In a study by Becker and Rudolf (2018), almost half of respondents reported having avoided a trip by private car due to free cargobike usage. Cargobike usage, however, is still limited to a fairly narrow audience. Dorner and Berger (2020) contend that 'men, well-educated people, and cyclists are particularly interested in cargobikes and cargobike-sharing' (p. 9).
- **Shared e-scooters**. While e-scooters may do more harm than good, especially if replacing trips by non-car modes, they may function as a viable first- and last-mile alternative (Hosseinzadeh et al., 2021), by increasing the catchment area of public transport services (Shaheen, & Chan, 2016). In addition to environmental concerns (Eccarius & Lu, 2020), a preference for trip efficiency and individual convenience have been identified as key adoption motives (Kopplin et al., 2021; Mitra & Hess, 2021).

Attitudinal factors were derived based on a combination of Diffusion of Innovation (Rogers, 1995) and Theory of Planned Behaviour (Ajzen, 1991) elements.

In addition to personal characteristics of the potential adopter (i.e., the decision-making unit), the former focuses on the perceived characteristics of the innovation (e.g., the perceived advantage or complexity of the innovation), whereas the latter is more concerned with behavioural, normative, and control beliefs regarding the use of the innovation, which are crucial in forming a behavioural intention to enact the target behaviour (i.e., adopt or not). Combining the two theories to derive attitudinal statements thus allows covering both, perceived aspects of the innovation as well as personally held beliefs of the decision-maker.

Diffusion of Innovation. Based on Everett Rogers' Diffusion of Innovations (DOI) theory (Rogers, 1995), it is assumed that the adoption of an innovation is driven by both people's individual characteristics (here: socio-demographic and travel related factors) as well as the perceived characteristics of the innovation, leading to either adoption or rejection of the innovation (see Fig. 1). The current study is therefore focused on Stages 1 to 3 of the adoption process. In the absence of behavioural measures or observations in the present study, adoption is operationalised as the perceived personal likelihood of adoption (i.e., extremely unlikely to extremely likely to use).

The perceived characteristics of the innovation can be summarised as the perceived **Relative Advantage (RA)** that the innovation provides over the product or service it replaces; the perceived **Compatibility (CO)** with the users' values, needs and characteristics; the perceived **Complexity (CX)** of the innovation (i.e., whether the innovation is easy to use and/or understand); **Trialability (TR)** of the innovation (i.e., whether potential adopters have the opportunity to experiment with or test the innovation before making the decision to adopt or not); and lastly, **Observability (OB)** or the extent to which the innovation produces tangible results. Importantly, it should be noted that, in the present study, the authors did not focus on the perceived characteristics of each shared electric vehicle type, but rather considered the perceived characteristics of shared mobility in general.

Theory of Planned Behaviour. The Theory of Planned Behaviour (TPB) (Ajzen, 1991) is a commonly used theoretical framework which posits that the behavioural intention to enact a specific behaviour is

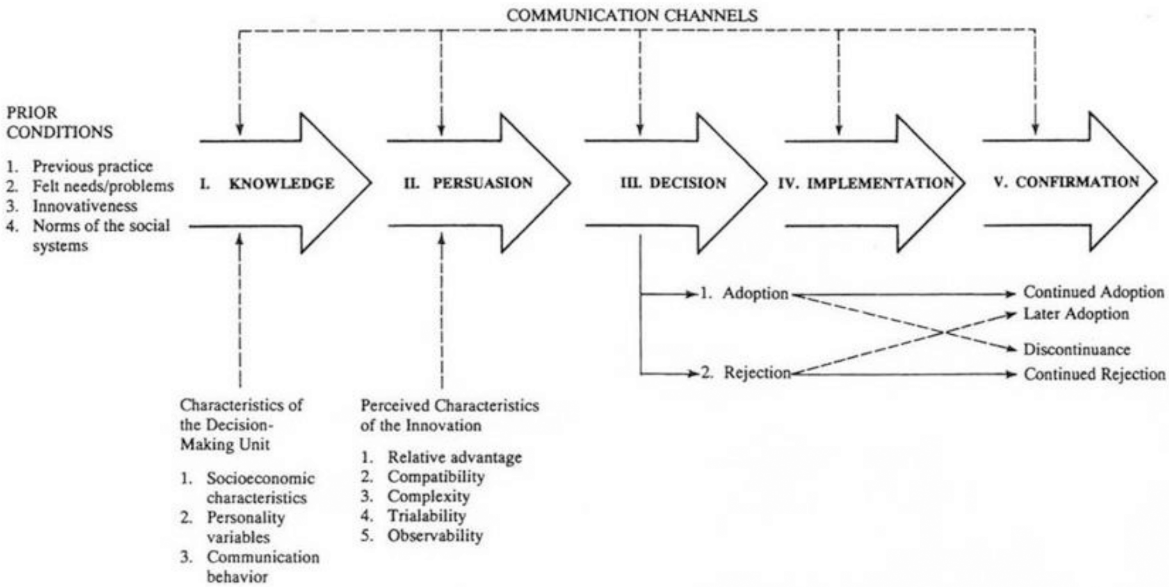

Fig. 1. The adoption process according to Diffusion of Innovations theory (Rogers, 1995).

determined by three interrelated factors (see Fig. 2): attitudes (i.e., either positively or negatively valanced behavioural beliefs regarding the target behaviour), subjective norms (i.e., whether others, whose opinion one values, approve or disapprove of the target behaviour), and perceived behavioural control (i.e., possessing the ability or capacity to enact the target behaviour).

Amongst its wide applications in the domain of travel behaviour (Ahmed et al., 2021; Donald et al., 2014; Lois et al., 2015; Neto et al., 2020), the TPB has also been applied in the context of shared mobility (Li et al., 2021; Mattia et al., 2019; Si et al., 2020; Yu et al., 2018). Instead of providing a test of the theory (e.g., Li et al., 2021; Si et al., 2020), however, the primary purpose of TPB in the present study was to derive attitudinal statements capturing respondents' personal attitudes, subjective norm, and perceived behavioural control, therefore complementing the perceived characteristics of the innovation based on DOI as potential predictors of adoption.

3. Method

In this section, the general approach of our research is introduced, including a description of the participant sample (Section 3.1), as well as the questionnaire and applied statistical analysis methods (Section 3.2). Ethical approval was obtained from the Newcastle University Ethics Committee.

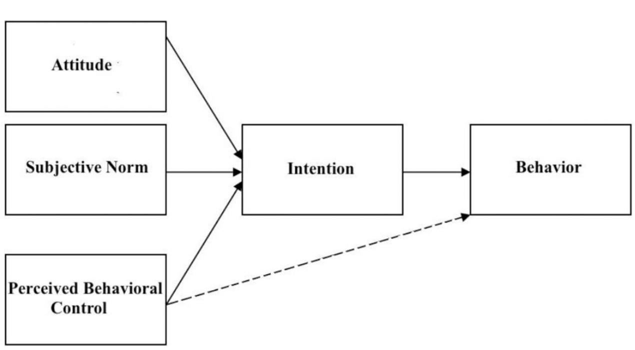

Fig. 2. The Theory of Planned Behaviour (Ajzen, 1991).

3.1. Participant sample

The online questionnaire was distributed in the seven pilot cities of the eHUBS project between March and December 2020, representing five European countries with vastly different travel behaviour (see Table 2). For instance, whereas cycling is common in a Dutch context (>25 % of all trips in Amsterdam, Arnhem, and Nijmegen), it only represents a small proportion of the modal share in Dreux or Manchester (3 %), whereas Leuven and Kempten tend to lie somewhere in the middle. The minimum sample size for each of the seven pilot cities was determined by using the sample calculator proposed by Ortúzar and Willumsen (2011). Table 2 presents the minimum recommended and achieved sample sizes. Please note that the cities of Nijmegen and Arnhem are considered as one city/region due to their geographical proximity (10 miles or about 16 km distant from each other).

In total, 2540 respondents completed the online questionnaire. Of those who finished the survey, 47 (2 %) did not complete all questionnaire sections and were thus removed for further analysis, leaving a final survey sample of 2493 respondents. The majority of respondents were recruited from the seven eHUBs pilot cities ($N = 2064$, 83 %), whereas the remainder reported living in different cities which were, however, located in one of the five target countries ($N = 414$, 17 %). The latter were distributed as follows: Germany ($n = 176$), France ($n = 133$), Belgium ($n = 37$), England ($n = 36$), and Netherlands ($n = 29$). The

Table 2
Modal shares (private car use and cycling for all trips) and recommended sample size for each eHUBS pilot city.

City	Car use	Cycling	Population	5 % error	Achieved sample	Deviation
Amsterdam	20 %[1]	33 %[1]	1,157,519[2]	385	466	+21 %
Leuven	50 %[3]	17 %[3]	102,275[4]	383	405	+6%
Manchester	71 %[5]	3 %[5]	576,500[6]	384	368	−4%
Kempten	59 %[7]	11 %[7]	68,940[4]	383	303	−21 %
Nijmegen/ Arnhem	48 %[8]	26 %[8]	172,000[9]/ 162,424[4]	384	267	−30 %
Dreux	54 %[10]	3 %[11]	30,664[4]	380	255	−33 %

online survey was distributed via each city's own distribution channels (e.g., e-mail invitation, social media, or website), whereas respondents in the two largest pilot cities (i.e., Amsterdam and Manchester) were recruited via a polling agency ($N = 834$ or 33 %). While the recruitment via polling agencies allowed for more control in terms of the sample composition, respondents tended to be younger, full-time employed, and highly educated in the professionally recruited samples, thus showing no substantial deviations from the samples recruited through the cities' own efforts. For more information on the sample composition of each city, we would like to refer the reader to a summary report of the first eHUBs survey (Bösehans et al., 2021a; Bösehans et al., 2021b).

As the recommended sample size could only be achieved for two pilot cities, respondents were grouped by their country of residence instead (i.e., Belgium, France, Germany, The Netherlands, and the UK), thus also including respondents from other cities of the same country in the analysis. The latter included a mix of mostly urban, but also some rural, areas scattered around the pilot cities. While this aggregation reduced the specificity of the analysis, it also simplified it (i.e., comparison between five countries rather than six cities), while simultaneously providing greater statistical confidence through increased sample size.

Demographic data for participants are provided in Table 3. Please note that all demographic questions were optional; hence, totals may not always add up to the full sample size. Compared to the EU average (last column), older respondents (i.e., 65 +) were underrepresented (9 % vs 21 %), as were female respondents, albeit to a lesser degree (46 % vs 51 %). In terms of household composition, households with two adults were overrepresented (51 % vs 31 %), whereas households with three or more adults were underrepresented (19 % vs 36 %). With regard to children in the household, there were more households with children in the sample compared to the EU average (47 % vs 30 %). The employment rate was comparable to the EU average (71 % vs 67 %), although the share of those having completed tertiary (i.e., university level) education was substantially greater (68 % vs 36 %). Finally, in terms of annual household income, no comparable EU statistics were available. Based on the UK median household income (£29,900), however, it is estimated that high incomes are overrepresented compared to low incomes.

Importantly, for the purpose of the present study, respondents were also asked about their shared mobility use. In total, the majority of respondents indicated that they are not currently using any form of shared mobility ($n = 1869$, 75 %), whereas the remainder reported having used either carsharing ($n = 349$, 14 %), bikesharing ($n = 247$, 10 %), e-scooters ($n = 117$, 5 %), and/or other shared modes ($n = 71$, 3 %). Both, survey data from current shared mobility users and non-users was used for the regression analyses, as shared electric vehicles provided via eHUBs may also present a novelty to users, thus providing insights on whether the latter would be willing to switch to eHUBs or not.

Table 3
Sample demographics; RG = Reference group; *equal to or older than 18 years.

Variable	Categories	Count (n)	Percent (%)	EU average
Age	18 to 24	287	11.5	64.1 (15–64 years) [12]
	25 to 34	620	24.9	
	35 to 44	551	22.1	
	45 to 54	468	18.8	
	55 to 64	337	13.5	
	65 to 74	179	7.2	20.81 [12]
	75 or older (RG)	49	2.0	
Gender	Male	1312	53.4	49[13]
	Female	1127	45.9	51[13]
	Other (RG)	16	0.7	–
Country	Netherlands	761	30.7	–
	Germany	478	19.3	
	Belgium	441	17.8	
	England	404	16.3	
	France	387	15.6	
	Other (RG)	7	0.3	
Number of adults in household*	1	735	29.9	33.9[14]
	2	1243	50.6	30.5[14]
	3	253	10.3	16.0[14]
	4 or more (RG)	226	9.1	19.6[14]
Number of children in household	0	975	52.6	70.2[15]
	1	348	18.8	14.1[15]
	2	366	19.8	11.8[15]
	3 or more (RG)	163	8.8	3.9[15]
Current occupation	School/Trainee/ Student	251	10.4	3.9[16]
	Employed (PT, FT, or Self)	1711	70.7	66.9[17]
	Home/ Unemployed/ Retired	406	16.8	7.3[17]
	Other (RG)	53	2.2	–
Education	Post- or undergraduate studies	1675	67.5	35.9[18]
	School education	430	17.3	45.5[18]
	Professional qualification	291	11.7	–
	No school education	15	0.6	18.6[18]
	Prefer not to say (RG)	73	2.9	–
Income	< £20,000	392	15.8	50 %[19]
	£20,000-£39,999	644	25.9	
	£40,000-£59,999	502	20.2	50 %[19]
	£60,000-£79,999	272	10.9	
	£80,000-£99,999	139	5.6	
	> £100,000	103	4.1	
	Prefer not to say (RG)	435	17.5	–

3.2. *Survey measures and analysis*

In this research study, four separate Multiple Linear Regression (MLR) analyses were computed in IBM SPSS Statistics Version 27 to predict the intention to use shared e-bikes, e-cargobikes, e-scooters, and e-cars, respectively, using a combination of various attitudinal, demographic, and travel related variables.

In each case, the dependent variable represented respondents' intention to use the shared (L)EV in question, rated on a Likert scale ranging from 0 – Extremely unlikely to 100 – Extremely likely. Although Likert scales are generally ordinal, ordinal variables with five or more categories (here: 100) can be regarded as an ordinal approximation of a continuous variable and have been shown to be robust against deviations in terms of linearity and normality when used in general linear models (Kéry & Hatfield, 2003; Norman, 2010). Hence, in the regression models, the four dependent variables measuring intention were treated as continuous variables. For all four dependent variables, residuals were normally distributed, thus warranting the use of MLR as opposed to less powerful non-parametric alternatives (Kéry & Hatfield, 2003).

MLR predictors were entered using the backward stepwise method and consisted of survey respondents' object scores on three attitudinal components, demographic variables, such as age and gender, and travel-related factors, such as the availability of vehicles in the household and respondents' regular trip satisfaction (see Table 4). A description of how the three attitudinal components were derived is provided below. Travel related factors further included items such as the possession of a driver's license, frequency of use of four major transport modes (i.e., walking, cycling, private motorised, and public transport), as well as traveller identity (e.g., identifying oneself as a car driver or cyclist) which has been shown to be associated with both stated intentions and self-reported travel behaviour (Heinen, 2016). Regular trip satisfaction, like intention, was measured on a 100-point continuous Likert-scale ranging from 0 – Extremely dissatisfied to 100 – Extremely satisfied. Descriptive statistics of independent variables by country of residence are presented in Table A1 in the appendix.

Table 4
List of independent variables entered into the MLR using the backward method.

Independent variables	Categories	Reference group
Pro shared mobility	Stand. object score (from CATPCA)	-
Pro-environment	Stand. object score (from CATPCA)	-
Pro barriers	Stand. object score (from CATPCA)	-
Age	18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, 65 to 74	75 or older
Gender	Male, Female	Other
Country	Belgium, France, German, Netherlands, United Kingdom	Other
Number of adults	1, 2, 3	4 or more
Number of children	0, 1, 2	3 or more
Education	No school education, School education, Professional qualification, University degree	Prefer not to say
Income	< £20,000, £20,000-£39,999, £40,000-£59,999, £60,000-£79,999 £80,000-£99,999, > £100,000	Prefer not to say
Current occupation	In education/training (1): Secondary school education, Apprenticeship/ Traineeship, Part-time student, Full-time student Employed (2): Part-time employed, Full-time employed, Self-employed Not employed (3): Unemployed, Retired from work, Home/family as primary role	Other
Driver's license	Yes	No
Regular trip satisfaction	0–100 continuous Likert scale	–
Traveller identity	Car driver, Cyclist, Public transport user, Multimodal user	Walker
Private motorised transport Cycling for transport Walking for transport Public transport	Once per month or less, 2–3 times per month, 1–2 days per week, 3–4 days per week, 5 days per week or more	Never nowadays
Number of cars Number of bicycles Number of cargobikes Number of scooters, mopeds, or motorbikes	1, 2, 3 or more	0 - None

Attitudinal components were derived via a Categorical Principal Component Analysis or CATPCA (i.e., the equivalent of PCA for ordinal data; Linting et al., 2007) of 20 attitudinal statements, measured on a 7-point Likert scale (1 – Strongly disagree to 7 – Strongly agree).

Based on a review of previous literature, the 20 statements were created to reflect attitudes towards car use, the environment, and shared mobility (see also Table 5), all of which may have a potential impact on an individual's intention to adopt novel shared mobility services (Hinkeldein et al., 2015). Several items were derived based on Everett Rogers' Diffusion of Innovation (DOI) Theory Rogers (2010) to measure people's attitudes towards the innovation (in this study: the potential use of shared [L]EVs from eHUBs), which may influence uptake. The remaining attitudinal items were based on Ajzen's Theory of Planned Behaviour (TPB; Ajzen, 1991), measuring people's intention to adopt eHUBs, perceived behavioural control, and subjective (or social) norms.

3.2.1. Categorical principal component analysis (CATPCA)

The underlying principle of PCA is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, whilst retaining as much as possible of the variation present in the data set (Atchley, 2007; Jolliffe, 1986). This is achieved by deriving a new, smaller set of independent (i.e., uncorrelated) variables, the principal components, which retain most of the variation present in all of the original variables.

Here, CATPCA was chosen for the factoring of data because, despite equidistance often being assumed between the different levels of Likert-scales, other commonly used dimension reduction techniques, such as Exploratory Factor Analysis (EFA) or PCA, are not appropriate for the use with ordinal data (Linting et al., 2007). A balanced factor solution was achieved, and thus large discrepancies in terms of explained variance between components avoided, by applying Varimax rotation which

Table 5
Rotated categorical component loadings and reliability estimates.

Attitude statements / Statistics	Measured construct	CC1	CC2	CC3
Cronbach's alpha (α)	Reliability	0.82	0.79	0.80
Explained variance	Variance	0.18	0.17	0.15
(Eigenvalue / number of items)				
1. I would enjoy trying out and using different electric vehicles from an eHUB.	Trialability #1 (DOI)	0.79		
2. I'd be interested in using eHUBs for commuting trips when they've become available in my city.	Adoption intention for commute (TPB)	0.78		
3. I'd be interested in using eHUBs for non-work trips when they've become available in my city.	Adoption intention for leisure (TPB)	0.77		
4. Shared mobility options provide me with more flexibility in the way I travel.	Relative advantage #1 (DOI)	0.70		
5. I am confident that, if I wanted to, I could use eHUBs without problems.	PBC eHUBs (TPB)	0.65		
6. I am often among the first people to experiment with new technologies.	Affinity for technology	0.53		
7. I would rather wait for other people to try eHUBs before I use them.	Trialability #2 (DOI)		0.77	
8. Shared mobility solutions like eHUBs are too complicated for me to use.	Complexity #1 (DOI)		0.73	
9. Shared mobility options cannot fulfil my mobility needs.	Perceived compatibility (DOI)		0.70	
10. I prefer travelling the way I am used to rather than using eHUBs.	Habit		0.69	
11. There is no point in using shared mobility options if you already own a car.	Relative advantage #2 (DOI)		0.68	
12. I do not feel confident to use an electric car.	PBC e-car (TPB)		0.54	
13. People should be allowed to use their cars as much as they like, even if it causes damage to the environment.	Car use attitude #1 (TPB)		0.49	
14. Almost every-one around me owns a private car.	Perceived social norm		0.29	
15. For the sake of the environment, every-one should reduce how much they use cars.	Car use attitude #2 (TPB)			0.78
16. I feel a moral obligation to reduce my emissions of greenhouse gases.	Personal norm			0.76
17. Congestion, air pollution and noise from road traffic is a real problem in my city.	Environment attitude #1 (TPB)			0.64
18. People around me find it important to reduce emissions of greenhouse gases.	Perceived subjective norm (TPB)			0.60
19. People who drive cars that are better for the environment should pay less to use the roads.	Car use attitude #3 (TPB)			0.52
20. I feel confident to ride an electric bicycle.	PBC e-bike (TPB)			0.43

produces independent (i.e., uncorrelated) component scores for each individual. As in ordinary PCA, each individual case receives a standardised score on each of the extracted components, called factor or 'object' scores. In our analysis, the normalised object scores for each individual were saved for use in the subsequent MLR analyses. The results of the CATPCA are presented below (Table 5). Taken together, the three extracted attitudinal components were interpreted by the team of authors to reflect holding a positive attitude towards and expressing an interest in shared mobility (CC1 – Pro-shared), perceived barriers to uptake (CC2 – Pro-barriers), and environmental or normative aspects (CC3 – Pro-environment). The Pro-shared mobility component encompassed various DOI and TPB elements thought to *positively* influence uptake, such as believing that shared mobility offers more flexibility, expressing an interest in using eHUBs for commute or non-work-related trips, and feeling confident in the use of eHUBs. The Pro-barriers component, on the other hand, consisted of various DOI and TPB elements that might *negatively* affect uptake, such as a pro-car attitude, lack of confidence in riding electric cars, incompatible mobility needs, or believing that eHUBs would be too complicated to use. Finally, the Pro-environment component was associated with awareness of environmental problems, beliefs in the importance of reducing car use and carbon emissions, as well as feeling confident to ride an electric bicycle.

3.2.2. *Multiple linear regression (MLR)*

In MLR, a quantitative dependent variable (Y) is explained by a function of multiple independent variables, which are thought to have a relationship with Y. Multiple regression equations generally take the form of: $Y = a + bU + cV + dW + eX + \ldots$, and are linear (i.e., Y is linear in the variables U, V, …), where the lowercase letters represent either positive or negative constants and the capital letters stand for independent variables (see Cohen et al., 2003). The prediction of Y occurs through the simple addition of the constant a and certain amounts (i.e., b, c, …) of each variable. In MLR, there is no constraint on the nature of the independent variables, which can take various shapes, from rectilinear (i.e., straight line), to curvilinear (i.e., nonlinear), or no specific shape at all. As computing a MLR model with a large number of predictors, including potentially irrelevant ones, is likely to lead to an overly complex model, a stepwise regression method was chosen to facilitate variable selection.

Variable selection. Stepwise regression facilitates the selection of essential variables to obtain a simpler and more easily interpretable regression model. To determine which variables to add or remove from the four MLR models, *backward stepwise selection* was chosen. With this particular method, variables are removed from the model until all of the remaining variables to be considered have a p-value smaller than a predefined threshold (i.e., usually $p = 0.05$). In contrast to other variable selection methods, such as forward selection, the *backward method* considers the effects of all variables simultaneously in a full model. This is particularly important in the case of collinearity (i.e., correlations among variables), because backward selection may have to keep all predictors in the model, unlike forward selection, where none of them might be entered in the first place. For a step-by-step description of the backward stepwise regression method, which has been found to produce slightly more accurate and parsimonious results (i.e., either comparable or higher accuracy with fewer variables selected) compared to the stepwise AIC method (Sanchez-Pinto et al., 2018), please see Choueiry (2021).

4. Results

The subsequent sections include a preliminary analysis of outcome measures by country of residence (Section 4.1) and presentation of regression results (Section 4.2).

4.1. *Preliminary analysis*

First, attitudinal factor scores, regular trip satisfaction, and the intention to use each of the four different shared electric vehicle types, were compared across countries using one-way ANOVAs with least significant difference (LSD) post-hoc comparisons (Williams & Abdi, 2010; see Table 6). This analysis revealed that, in terms of attitudinal factors, German respondents were most favourable towards shared mobility, whereas Belgian and British respondents were the least favourable. German respondents also perceived the least barriers towards shared mobility use, whereas the opposite was the case for British respondents. Finally, German and Belgian respondents evidenced the most pro-environmental attitude. As concerns regular trip satisfaction, respondents from Germany and France reported being significantly less

Table 6
Mean comparison of attitudinal factors, regular trip satisfaction, and intention to use different types of shared electric vehicle by respondents' country of residence.

Mode	Intention	NL	FR	GER	BE	UK	Total
Pro-shared	Mean	0.03_{a}	$0.09_{a,b,c}$	0.20_{c}	-0.19_{d}	-0.14_{d}	0
	Median	0.15	0.13	0.28	−0.08	0.03	0.10
	N	761	387	478	441	404	2493
Pro-barriers	Mean	0.08_{a}	0.07_{a}	-0.58_{b}	-0.12_{c}	0.61_{d}	0
	Median	0.26	0.12	−0.55	0.04	0.84	0.17
	N	761	387	478	441	404	2493
Pro-environment	Mean	-0.10_{a}	-0.12_{a}	0.25_{b}	0.29_{b}	-0.30_{c}	0
	Median	−0.05	−0.16	0.26	0.41	−0.33	0.01
	N	761	387	478	441	404	2493
Regular trip satisfaction	Mean	77.78_{a}	71.47_{b}	71.57_{b}	80.64_{c}	$77.98_{a,c}$	76.18
	Median	80	77	80	85	79	80
	N	743	376	451	433	402	2724
e-bike	Mean	53.51_{a}	61.92_{b}	49.5_{c}	43.55_{d}	$47.78_{c,d}$	51.35
	Median	61	71	54	40	55	60
	N	762	390	481	441	407	2481
e-car	Mean	57.10_{a}	57.61_{a}	57.65_{a}	48.50_{b}	54.41_{a}	55.32
	Median	64	67	69	55	61.5	63
	N	760	385	478	437	404	2464
e-cargo	Mean	$49.22_{a,b,c}$	45.80_{a}	$46.69_{a,c}$	32.07_{b}	40.54_{c}	42.57
	Median	66.5	49	50	20	39	40
	N	18	370	166	113	399	1066
e-scooter	Mean	$49.61_{a,b,c}$	53.16_{b}	41.38_{a}	32.57_{c}	41.09_{a}	44.56
	Median	60.5	55	30	18.5	39	42.5
	N	18	368	165	112	399	1062

Note: Mean values with different subscript letters differ significantly from each other at $p < 0.05$. For instance, the e-bike mean of the Netherlands (a) is significantly different from all other means, whereas Germany (c) and Belgium (d) differ significantly from each other but are indistinguishable from the UK (therefore: c,d).

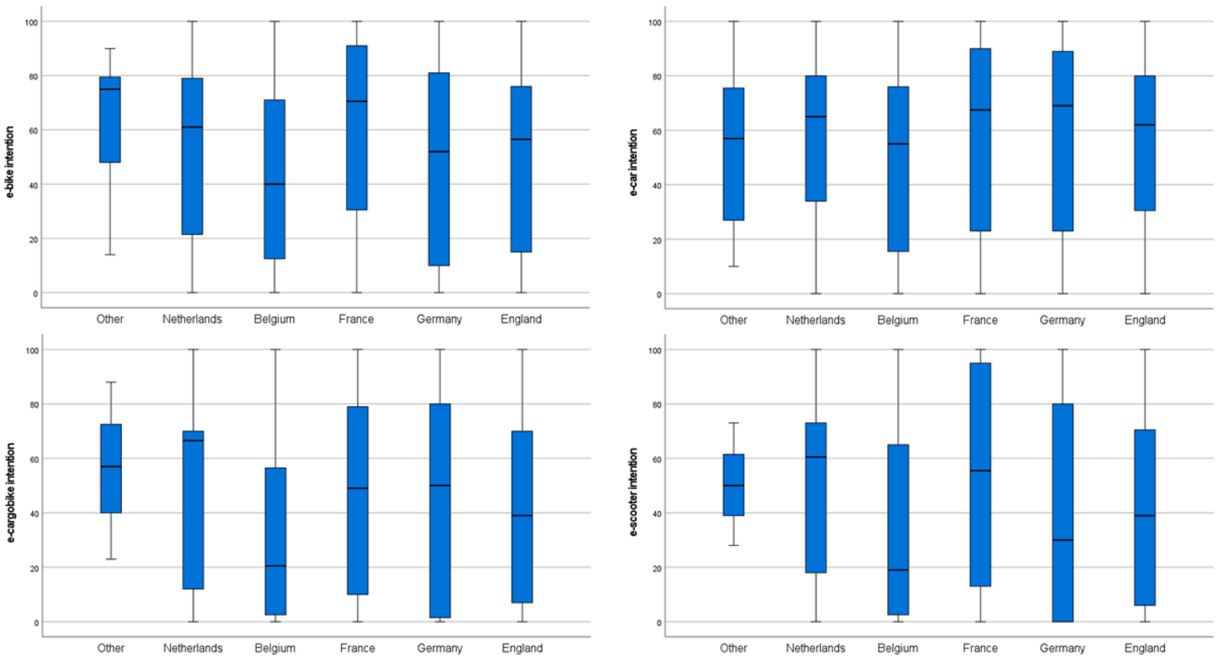

Fig. 3. Boxplot of intention to use shared e-bikes (top left), e-cargobikes (bottom left), e-cars (top right), and e-scooters (bottom right) (ranging from 0 – Extremely unlikely to 100 – Extremely likely continuous Likert scale) by country of residence.

satisfied than respondents from either Belgium, the Netherlands, or the UK. Coincidentally, respondents from Germany and France also reported the highest levels of private car use (79 % using PMT at least 1–2 days per week) compared to substantially lower levels in Belgium (53 %), the Netherlands (54 %), and the UK (72 %). This suggests that increased levels of private car use may be detrimental to regular trip satisfaction. With regard to the willingness to use shared electric vehicles, shared electric cars were indeed more popular than either shared e-bikes, e-cargobikes, or e-scooters, with the only exception of France, where the e-bike was the most desired mode.

The reader should be aware that intention items for shared e-cargobikes and e-scooters were only added to the survey at a later date. With regard to e-scooters, this was the case due to legislation for e-scooters not yet being in place for some pilot cities at the time of data collection. With regard to e-cargobikes, not all pilot cities had planned to include the latter in the shared electric vehicle fleets, which led to their initial exclusion. Hence, at least initially, less data was available for these items compared to shared electric bicycles and cars. This was the case especially in the Netherlands, where data collection concluded earlier in comparison to pilot cities from other countries.

Comparing the mean intention to use shared electric vehicles across countries revealed some cultural and geographical differences (see Fig. 3). Regarding shared e-bikes, those living in the Netherlands expressed a greater use intention compared to all other countries except France. Respondents living in France, in fact, expressed a significantly greater interest in e-bikes than respondents from the Netherlands and also expressed the greatest interest in e-scooters. The former can perhaps be explained by the already high prevalence of cycling in the Netherlands, as Dutch residents may prefer to ride their own bicycles. The demand for shared e-cars was similar across most cities, while those resident in Belgium expressed the lowest intention to use any shared mobility mode. Table A2 in the appendix provides further mean values for comparison based on key variables of interest.

4.2. Regression results

General findings and cross-country differences are summarised below. Thereafter, the MLR results to predict the intention to use each of the four shared electric vehicle types, are presented in turn with β values serving as effect size estimates (see also Table 7 for a complete list of statistically significant predictors by mode).

- **General findings**. Across all modes, a pro-shared mobility attitude emerged as the strongest predictor of intention ($0.41 < \beta < 0.49$, $p < 0.001$), supporting the added value of both DOI and TPB elements as predictors of intention. While less in magnitude, holding a pro-environmental attitude also increased intention slightly ($0.06 < \beta < 0.12$, $p \leq 0.05$), whereas perceived barriers, expectedly, decreased intention ($-0.12 < \beta < -0.19$, $p < 0.01$). No differences among genders were observed, except for women showing a slightly greater intention to use shared e-bikes ($\beta = 0.05$, $p = 0.03$).
- **Country differences**. Overall, respondents from Belgium ($\beta = -0.10$, $p < 0.01$) and Germany ($\beta = -0.13$, $p < 0.001$) expressed a lower intention to use e-cargobikes. On the other hand, respondents from England, France, and the Netherlands, expressed a greater intention to use shared e-bikes, e-scooters, and e-cars ($0.08 < \beta < 0.16$, $p < 0.05$). Respondents living in France, in particular, expressed a strong desire to use e-bikes ($\beta = 0.15$, $p < 0.001$) and e-scooters ($\beta = 0.14$, $p < 0.01$), reaffirming the findings in Table 6, whereas respondents from England showed a stronger preference for shared electric cars ($\beta = 0.16$, $p < 0.001$).
- **Shared e-bikes.** Young adults (i.e., 18 to 34 years) showed a greater intention to use e-bikes ($0.05 < \beta < 0.06$, $p < 0.01$), as did respondents owning either one bicycle, up to two cars, or at least one motorbike ($0.05 < \beta < 0.08$, $p < 0.05$). The intention to use shared e-bikes was also greater among respondents who reported either cycling or using public transport, irrespective of frequency of use ($0.06 < \beta < 0.11$, $p < 0.05$). Finally, those with a university degree ($\beta = -0.07$, $p = 0.01$) and those in possession of a driver's licence ($\beta = -0.06$, $p = 0.01$) showed a lower intention to use shared e-bikes, whereas the opposite was the case for those with no school education ($\beta = 0.06$, $p < 0.01$).
- **Shared e-cargobikes.** Similar to the findings for shared e-bikes, regular cycling and public transport use were associated with a greater interest in using shared e-cargobikes ($0.07 < \beta < 0.25$, $p < 0.05$), especially cycling on five days per week or more ($\beta = 0.25$, $p <$

Table 7
Significant multiple linear regression coefficients after using the backward stepwise procedure by shared electric vehicle type.

Variable	Shared e-bike (adj. $R^2 = 0.36$) b	β	p	Shared e-cargobike (adj. $R^2 = 0.40$) b	β	p	Shared e-scooter (adj. $R^2 = 0.35$) b	β	p	Shared e-car (adj. $R^2 = 0.37$) B	β	p
Constant	34.64		0.00	53.93		0.00	43.86		0.00	34.28		0.00
Pro shared mobility	16.05	0.48	0.00	15.30	0.46	0.00	13.88	0.41	0.00	15.95	0.49	0.00
Pro perceived barriers	−6.12	−0.18	0.00	−6.27	−0.17	0.00	−4.60	−0.12	0.00	−6.25	−0.19	0.00
Pro-environment	2.84	0.08	0.00	3.89	0.10	0.00	2.50	0.06	0.05	3.92	0.12	0.00
Age = 18 to 24	7.24	0.07	0.01				16.47	0.17	0.00	5.44	0.05	0.02
Age = 25 to 34	5.14	0.06	0.01				12.82	0.16	0.00			
Age = 35 to 44							11.77	0.15	0.00			
Gender = Female	3.22	0.05	0.03									
Country = Belgium				−10.26	−0.10	0.00						
Country = Germany	−5.02	−0.05	0.05	−14.48	−0.13	0.00						
Country = France	16.53	0.15	0.00				11.84	0.14	0.00	8.79	0.08	0.00
Country = England	6.94	0.09	0.01				7.62	0.11	0.01	12.54	0.16	0.00
Country = Netherlands	4.46	0.06	0.04							8.36	0.12	0.00
Number of adults = 1				−10.11	−0.13	0.01				−4.81	−0.07	0.04
Number of adults = 2				−9.27	−0.13	0.01				−3.89	−0.06	0.06
Number of adults = 3				−9.88	−0.09	0.03						
Number of children = 0				−4.75	−0.07	0.06				−3.33	−0.05	0.04
No school education	34.39	0.06	0.00							27.34	0.05	0.01
School education							−16.96	−0.22	0.01			
University degree	−4.95	−0.07	0.00				−17.84	−0.25	0.00			
Income = £60,000-£79,999				−8.97	−0.08	0.02						
Income =/> £100,000										−6.88	−0.04	0.04
Driver's licence = Yes	−6.57	−0.06	0.01							21.82	0.22	0.00
Frequency PMT =/< Opm[1]							−10.12	−0.06	0.06			
Frequency PMT = 1–2 dpw[3]										3.85	0.05	0.03
Frequency CYC =/< Opm	10.61	0.09	0.00									
Frequency CYC = 2–3 tpm[2]	9.69	0.08	0.00	9.03	0.08	0.02	10.91	0.09	0.01			
Frequency CYC = 1–2 dpw	8.72	0.10	0.00				10.72	0.11	0.00			
Frequency CYC = 3–4 dpw	5.88	0.06	0.03	7.97	0.07	0.05						
Frequency CYC =/> 5 dpw	6.09	0.08	0.02	32.22	0.25	0.00						
Frequency PT =/< Opm	5.75	0.07	0.01									
Frequency PT = 2–3 tpm	9.73	0.11	0.00									
Frequency PT = 1–2 dpw	8.65	0.09	0.00	9.52	0.08	0.01						
Frequency PT = 3–4 dpw	10.07	0.09	0.00	9.81	0.08	0.01	14.36	0.12	0.00			
Frequency PT =/> 5 dpw	10.72	0.09	0.00				15.44	0.12	0.00			
Number of cars = 1	5.28	0.08	0.01									
Number of cars = 2	6.04	0.07	0.02									
Number of bikes = 1	3.96	0.05	0.04									
Number of bikes = 3 or more	−4.91	−0.07	0.01	−9.17	−0.12	0.00				−5.41	−0.08	0.00
Number of cargobikes = 1				10.84	0.07	0.04				6.34	0.05	0.02
Number of motorbikes = 1	4.74	0.05	0.03									
Number of motorbikes = 3 or more	15.26	0.06	0.01							14.41	0.06	0.01

PMT = Private Motorised Transport; CYC = Cycling; PT = Public transport.
Reference groups: Age (75 or older); Gender (Other); Country (Other); Number of adults (4 or more); Number of children (3 or more); Education (Prefer not to say); Income (Prefer not to say); Driver's license (No); Frequency (Never nowadays); Number of vehicles (0 - None).
[1] Opm = Once per month; [2] tpm = times per month, [3] dpw = days per week.

0.001). Compared to the reference group (i.e., four or more adults in the household), having fewer household members decreased the interest in e-cargobikes (-0.09 < β < -0.13, $p < 0.05$), as did living in a household without children (β = -0.07, $p = 0.057$), and earning an income between £60,000-£79,999 (β = -0.08, $p = 0.02$). Finally, existing cargobike owners showed a greater interest in using shared e-cargobikes (β = 0.07, $p < 0.05$).

- **Shared e-scooters.** Replicating earlier findings on shared e-bikes, young to middle-aged adults (i.e., 18 to 44 years) showed a greater intention to use e-scooters (0.15 < β < 0.17, $p < 0.001$), as did more frequent public transport users (i.e., those using public transport on 3–4 days per week or more; both β = 0.12, $p < 0.001$) and occasional cyclists (i.e., cycling 2–3 times per month or on 1–2 days per week; 0.09 < β < 0.11, $p < 0.01$). Again, holding a university degree, as well as having school education, was associated with a lower intention to use shared e-scooters (-0.22 < β < -0.25, $p < 0.01$).
- **Shared e-cars.** Apart from attitudinal and country-specific variables, the strongest predictor of using shared e-cars was holding a driver's licence (β = 0.22, $p < 0.001$). In terms of age, only the youngest age group (i.e., 18–24 years) showed a greater intention to use shared e-cars (β = 0.05, $p < 0.05$), whereas regular car drivers (i.e., using private motorised transport on 1–2 days per week) also indicated a greater intention to use e-cars (β = 0.05, $p = 0.03$). As was the case with shared e-cargobikes, having fewer household members compared to the reference group decreased the interest in shared e-cars (-0.06 < β < -0.07, $p \leq 0.06$), as did living in a household without children (β = -0.05, $p = 0.04$), and earning a high income (i.e., ≥ £100,000; β = -0.04, $p = 0.04$). Finally, owning a cargobike, and owning three or more motorbikes, was associated positively with intention (0.05 < β < 0.06, $p < 0.05$).

Table A1
Descriptive statistics of independent variables by country of residence.

Variable	Categories	Netherlands ($N = 761$)	France ($N = 387$)	Germany ($N = 478$)	Belgium ($N = 441$)	UK ($N = 404$)
Age	18 to 24	11 %	21 %	6 %	8 %	15 %
	25 to 34	26 %	26 %	25 %	19 %	28 %
	35 to 44	20 %	29 %	23 %	23 %	18 %
	45 to 54	20 %	16 %	23 %	18 %	15 %
	55 to 64	14 %	7 %	18 %	16 %	11 %
	65 to 74	8 %	1 %	4 %	13 %	7 %
	75 or older	2 %	< 1 %	1 %	2 %	5 %
Gender	Male	53 %	47 %	65 %	51 %	50 %
	Female	47 %	53 %	34 %	49 %	50 %
	Other	< 1 %	1 %	1 %	< 1 %	< 1 %
Number of adults*	1	36 %	26 %	23 %	33 %	27 %
	2	48 %	46 %	60 %	48 %	51 %
	3	7 %	16 %	11 %	9 %	12 %
	4 or more	8 %	13 %	7 %	10 %	10 %
Number of children	0	58 %	28 %	51 %	56 %	59 %
	1	20 %	9 %	22 %	19 %	19 %
	2	16 %	37 %	22 %	13 %	18 %
	3 or more	5 %	26 %	6 %	12 %	4 %
Education	Prefer not to say	2 %	9 %	3 %	1 %	1 %
	No school education	1 %	1 %	–	< 1 %	1 %
	School education	15 %	14 %	5 %	17 %	38 %
	Professional qualification	16 %	9 %	19 %	1 %	10 %
	University degree	66 %	67 %	73 %	80 %	50 %
Income	Prefer not to say	14 %	26 %	23 %	20 %	7 %
	< £20,000	15 %	27 %	6 %	9 %	23 %
	£20,000-£39,999	26 %	31 %	16 %	25 %	34 %
	£40,000-£59,999	21 %	13 %	24 %	22 %	19 %
	£60,000-£79,999	12 %	2 %	16 %	14 %	9 %
	£80,000-£99,999	8 %	< 1 %	8 %	6 %	3 %
	> £100,000	4 %	–	7 %	4 %	5 %
Current occupation	School, Apprentice/ Trainee, FT/PT Student	10 %	18 %	6 %	8 %	11 %
	Full-time, part-time, or self-employed	71 %	68 %	85 %	70 %	57 %
	Unemployed, Retired, Home/ family role	15 %	12 %	8 %	20 %	31 %
	Other	3 %	2 %	1 %	3 %	1 %
Driver's license	Yes	88 %	16 %	98 %	88 %	19 %
	No	12 %	84 %	2 %	12 %	81 %
Satisfaction	Regular trip	77.8	71.5	71.6	80.6	77.9
Identity	Car driver	30 %	63 %	32 %	17 %	57 %
	Cyclist	27 %	4 %	20 %	37 %	4 %
	Walker	7 %	10 %	5 %	7 %	16 %
	Public transport user	10 %	9 %	2 %	7 %	10 %
	Multimodal user	26 %	15 %	41 %	33 %	13 %
PMT use	Never	17 %	13 %	2 %	11 %	16 %
	Opm or less	15 %	4 %	7 %	16 %	5 %
	2–3 tpm	14 %	4 %	13 %	21 %	7 %
	1–2 dpw	23 %	10 %	25 %	31 %	23 %
	3–4 dpw	18 %	13 %	17 %	10 %	22 %
	5 dpw or more	13 %	56 %	37 %	12 %	27 %
Walking	Never	7 %	25 %	4 %	7 %	20 %
	Opm or less	7 %	11 %	6 %	10 %	9 %
	2–3 tpm	11 %	11 %	11 %	10 %	13 %
	1–2 dpw	23 %	14 %	26 %	21 %	22 %
	3–4 dpw	21 %	12 %	21 %	21 %	15 %
	5 dpw or more	31 %	27 %	31 %	33 %	21 %
Cycling	Never	12 %	62 %	8 %	13 %	56 %
	Opm or less	8 %	13 %	14 %	6 %	9 %
	2–3 tpm	10 %	8 %	13 %	5 %	9 %
	1–2 dpw	18 %	8 %	22 %	16 %	13 %
	3–4 dpw	21 %	4 %	17 %	15 %	7 %
	5 dpw or more	31 %	5 %	27 %	47 %	5 %
PT use	Never	13 %	66 %	21 %	11 %	33 %
	Opm or less	24 %	9 %	41 %	31 %	22 %
	2–3 tpm	19 %	3 %	17 %	22 %	14 %
	1–2 dpw	19 %	6 %	9 %	11 %	13 %
	3–4 dpw	16 %	3 %	5 %	14 %	11 %
	5 dpw or more	10 %	13 %	8 %	12 %	7 %
N Cars	0	30 %	13 %	10 %	29 %	16 %
	1	55 %	37 %	43 %	51 %	60 %
	2	14 %	39 %	35 %	17 %	20 %
	3 or more	1 %	11 %	12 %	3 %	4 %
N Bikes	0	6 %	22 %	4 %	8 %	46 %
	1	29 %	24 %	10 %	19 %	29 %
	2	27 %	21 %	27 %	25 %	15 %

(*continued on next page*)

Table A1 (*continued*)

Variable	Categories	Netherlands (N = 761)	France (N = 387)	Germany (N = 478)	Belgium (N = 441)	UK (N = 404)
	3 or more	38 %	33 %	59 %	48 %	10 %
N Cargo	0	82 %	97 %	93 %	87 %	93 %
	1	13 %	2 %	5 %	11 %	5 %
	2	3 %	–	1 %	1 %	1 %
	3 or more	2 %	1 %	1 %	1 %	1 %
N Scooter	0	75 %	80 %	72 %	90 %	88 %
	1	20 %	14 %	22 %	7 %	8 %
	2	3 %	4 %	3 %	2 %	2 %
	3 or more	1 %	2 %	3 %	1 %	< 1 %

Table A2
Mean (median) intention to use each shared mode by demographic variables.

Variable	Categories	e-bike	e-car	e-cargobike	e-scooter
Age	18 to 24	62.8 (69)	60.6 (68)	49.6 (51)	62.1 (71)
	25 to 34	56.7 (65)	60.6 (69)	48.6 (50)	52.7 (57)
	35 to 44	54.1 (64)	57.5 (65)	46.4 (50)	47 (50)
	45 to 54	46.6 (50)	52.9 (60)	38.1 (25.5)	35.9 (25.5)
	55 to 64	44.3 (48)	48.7 (51)	30.5 (22.5)	23.5 (4.5)
	65 to 74	35.3 (23)	44.4 (47.5)	18.9 (5)	17.1 (3)
	75 or older	28.7 (12)	37.2 (37)	22.8 (7)	16 (3.5)
Gender	Male	49.8 (58)	55.9 (64)	42.6 (39)	46.5 (50)
	Female	52.5 (60)	54.5 (62)	42.2 (40)	42.1 (37)
Country	Netherlands	53.5 (61)	57.2 (65)	49.2 (66.5)	49.6 (60.5)
	Germany	49.2 (52)	57.6 (69)	46.7 (50)	41.8 (30)
	Belgium	43.5 (40)	48.5 (55)	32.3 (20.5)	32.8 (19)
	England	48 (56.5)	54.7 (62)	40.7 (39)	41.2 (39)
	France	61.9 (70.5)	57.8 (67.5)	45.9 (49)	53.3 (55.5)
Number of adults*	1	50.7 (58)	52.7 (59)	42.4 (42)	46.1 (50)
	2	49.5 (58)	54.4 (63)	40.3 (35)	40.2 (31)
	3	53.2 (60)	60.6 (70)	44.2 (44.5)	49.9 (52)
	4 or more	58.6 (66.5)	62.4 (70)	49.9 (54.5)	52.6 (63)
Number of children	0	46.5 (50)	51 (57)	37.4 (30)	38.9 (30)
	1	55.1 (63)	60.7 (68)	45 (44)	49.5 (51)
	2	57.6 (69.5)	59.5 (67)	50.4 (54)	53.4 (60)
	3 or more	54.5 (62)	58.4 (69)	50.2 (50)	51.6 (55)
Education	No school education	72.4 (75)	54.7 (53)	42.2 (44)	60.6 (58.5)
	School education	48.3 (56)	49.1 (52.5)	36.4 (27.5)	37.5 (28)
	Professional qualification	54.6 (63)	56.6 (64)	46.3 (50)	46.7 (49)
	University degree	50.9 (59)	56.6 (65)	44.1 (42.5)	46.4 (50)
Income	< £20,000	54.5 (64)	51.8 (57)	42.3 (37)	48.7 (50)
	£20,000-£39,999	52.4 (60)	56.9 (65)	40.4 (34)	43 (42)
	£40,000-£59,999	51.4 (61)	57.7 (66)	46 (50)	45.4 (48)
	£60,000-£79,999	48.8 (57.5)	57.5 (68)	39 (31.5)	42 (41.5)
	£80,000-£99,999	57.2 (70)	63.8 (70.5)	48.1 (50)	41.4 (37)
	> £100,000	51.1 (61)	52.8 (58)	54.4 (57.5)	49.8 (52)
Current occupation	School, Apprentice/ Trainee, FT/PT Student	64.6 (71)	59.3 (68)	52.9 (56)	62.8 (71)
	Full-time, part-time, or self-employed	51.8 (60)	57.5 (65)	43.7 (47)	45.2 (44)
	Unemployed, Retired, Home/family role	41.6 (33)	44.5 (50)	32.8 (22)	31.7 (17.5)
Driver's license	Yes	50.6 (59)	57.9 (66)	42.4 (40)	43 (39)
	No	55.9 (65)	34.7 (27)	42.9 (39)	53 (64)
Identity	Car driver	50.4 (60)	56.6 (65)	39 (30)	43.7 (40)
	Cyclist	49.2 (55)	55.3 (62)	59.9 (67)	43.7 (43)
	Walker	50.3 (57.5)	44.2 (42)	37.2 (35.5)	42.7 (43)
	Public transport user	54.4 (64)	48.7 (54)	46.2 (45)	55.2 (65.5)
	Multimodal user	53.1 (60)	58.8 (66)	48.3 (50)	43.6 (38)

5. Discussion

In this study, current users' and non-users' intentions to use four different shared electric vehicle types were analysed in five European countries, advancing research on the potential added value of shared electric mobility hubs with diverse shared mobility options.

A first major observation relates to the effect of a *pro-shared mobility attitude* which was the strongest predictor of the intention to use any of the four shared vehicle types. Pro-environmental or normative aspects, perceived barriers, and various demographic or travel-related factors, were also significant predictors, yet were largely overshadowed by the predictive power of a pro-shared mobility attitude. Those scoring high on the pro-shared component are interested in using shared vehicles for either commuting or leisure trips, feel confident about the use of eHUBs and shared electric vehicles (i.e., high PBC), and believe in the added benefits of shared mobility, such as increased flexibility (see also Table 5). These results demonstrate that both, the perceived characteristics of the innovation (Rogers, 1995), as well as behavioural beliefs (i.e., a pro-shared mobility attitude) are crucial for the intended uptake of any shared (electric) vehicle type (Ge et al., 2020; Li et al., 2021; Mattia et al., 2019; Yu et al., 2018), thus lending support to both DOI and TPB constructs.

A *pro-environmental attitude* increased the intention to use shared electric vehicles (see also Garaus and Garaus, 2021; Li & Kamargianni, 2020), including e-scooters, as demonstrated in past research (Eccarius & Lu, 2020; Kopplin et al., 2021; Mitra & Hess, 2021). Expectedly, respondents who scored higher on the *perceived barriers* component, reflecting a negative shared mobility but pro-car attitude, and lack of confidence toward shared mobility use, evidenced lower intentions to use shared electric vehicles. In line with previous research, these findings suggest that private car ownership and low technological capabilities, especially among the older generations, are among the key barriers preventing shared mobility uptake (Alonso-González et al., 2020; Butler et al., 2020).

In terms of demographic variables, *age* was a significant predictor for the intention to use shared electric vehicles. This was especially the case for shared e-bikes and e-scooters, respectively, supporting previous research (Ge et al., 2020; Nikiforiadis et al., 2019). For shared e-cargobikes, there was no significant effect of age on intention, whereas only the youngest age group was associated with a greater intention to use shared electric cars. The latter suggests that shared electric cars and cargobikes might be more attractive to a broader range of age groups. For *gender*, contrary to previous studies that showed gender effects (Dorner & Berger, 2020; Jie et al., 2021; Ko et al., 2021; Reck & Axhausen, 2021), the authors did not find any influence of gender on respondents' interest in shared electric vehicles, with the exception of shared e-bikes, where female respondents showed slightly more interest. Beyond gender, respondents living in Dreux or Manchester showed greater interest in all e-modes, except shared e-cargobikes, compared to the reference group.

Owning at least one bicycle, car, or motorbike, further increased the intention to use *shared e-bikes*. In addition, those who were already cycling or using public transport, irrespective of the frequency of use, also showed a greater interest in shared e-bikes, which suggests that current cyclists and public transport users may be the most eager to use shared e-bikes as either a supplement to, or substitute for, their current mobility. Similarly, in the case of *e-cargobikes*, those cycling on at least 3–4 days per week expressed the greatest interest, whereas being an existing cargobike owner further increased the intention to use shared e-cargobikes (see also Dorner & Berger, 2020). Regular public transport users (i.e., those who use public transport on 1–2 or 3–4 days per week) also expressed a greater interest in e-cargobikes, reinforcing the suitability of the latter as an alternative for those without access to a private car (Becker & Rudolf, 2018).

In line with the above, occasional cyclists (i.e., cycling 2–3 times per month up to 1–2 days per week) and frequent public transport users (i.e., using on 3–4 days per week or more) reported a greater interest in *e-scooters*, indicating that e-scooters could either replace or supplement trips currently being made by bicycle or public transport (see also James et al., 2019). This research finding is particularly important due to the dubious environmental impact of e-scooters (Hollingsworth et al., 2019), whose lifecycle emissions tend to be substantially higher than the modes that are being replaced. Interestingly, despite previous research suggesting that the perceived greenness of e-scooters is lower compared to other shared mobility modes, such as shared e-bikes (Flores & Jansson, 2021), the intention to use e-scooters was positively predicted by holding a pro-environmental attitude. On the other hand, the possession of a driving licence, which is currently a requirement to ride e-scooters (at least in the UK), did not emerge as a significant predictor of intention.

Notably, while *shared electric cars* emerged as the most popular mode according to a comparison of intention means, only the youngest age group expressed a greater interest, suggesting that the age factor may be a lesser barrier to the use of shared electric cars. Alternatively, because those belonging to one of the older age groups tend to already own a car, therefore making it more difficult to change their habits, the younger generation may never want to own a car and prefer to always use shared vehicles. Apart from holding a positive attitude towards shared mobility, using private motorised transport and holding a driving licence had a significant effect on the intention to use shared e-cars, indicating that occasional car drivers may be willing to substitute some or most of their trips with shared electric vehicles. Shared e-cars were favoured by Dutch, French, and UK respondents.

Finally, of all the variables entered into the regression models – current occupation, the frequency of walking, regular trip satisfaction, and respondents' traveller identity – had no statistically significant influence on the intention to use any of the four shared electric vehicles types. With regard to respondents' traveller identity, this is particularly surprising, as traveller identity and travel behaviour tend to be closely related (Heinen, 2016). In our case, it is likely that traveller identity simply did not explain sufficient unique variance beyond the reported frequency of use of various transport modes.

5.1. Implications

In contrast to previous research (Claasen, 2020), our findings support the added value of eHUBs above and beyond common monomodal (car) sharing schemes, as different shared electric vehicle types were found to appeal to different groups of transport users and population segments. Shared e-bikes and e-scooters are particularly attractive to younger age groups, even if their potential to replace trips by private car appears limited (Bieliński et al., 2021; James et al., 2019). Instead, shared e-bikes and e-scooters should be regarded as an important part of the mobility agenda, creating more mobility options for young people, thereby aiding to prevent or at least delay car dependence. Interest in e-cargobikes appears to be limited to experienced frequent cyclists and regular public transport users who may use them as an alternative to the private car (Dorner & Berger, 2020). Yet, while more limited in their target audience, the untapped potential of e-cargobikes to replace trips by private car should not be underestimated (Becker & Rudolf, 2018). Finally, shared electric cars appear to be an attractive alternative to those driving occasionally (i.e., 1–2 days per week). Widespread adoption could shift more trips from private to shared cars (Firnkorn & Müller, 2015), ideally to the point of foregoing car ownership (Chapman et al., 2020), although the emission reduction potential may be limited due to a countries' energy mix (Faria et al., 2013), and to trips being replaced that were made previously by sustainable modes, which also applies to other shared mobility modes.

In summary, while the results of the present study do suggest that, due to their varied offer of shared electric modes, eHUBS may appeal to different demographic and mode user groups, the contribution to a reduction in road transport emissions and traffic congestion, as well as local air and noise pollution, may be limited in the short term. In the case of shared e-(cargo)bikes and e-scooters, this may be due to these modes appealing particularly to current cyclists and public transport users who may substitute some of their trips with shared modes. Hence, to achieve the desired long-term impacts, large scale deployment and close collaboration between local authorities and shared mobility providers will be required to determine the best hub locations and achieve sufficient uptake and use, such as by car dependent families (Bösehans et al., 2021a; Bösehans et al., 2021b), to ensure profitability. In addition, further restrictions to private car use may be necessary, such as reductions in private vehicle parking space or a prioritisation of shared electric vehicles in cities. eHUBs may also need to adapt to an increasingly ageing population (e.g., provision of new vehicle types for elderly) whose mobility needs differ from the rest of the population.

5.2. Limitations and future research

Our results indicate that different types of shared electric vehicles appeal to different audiences and therefore indirectly provide support for the added value of eHUBs over common monomodal shared mobility schemes. eHUBs provide several potential advantages over monomodal, station-based or free-floating, sharing schemes in that they facilitate intermodal mobility and can fulfil varied mobility needs through a diverse offer of shared electric vehicles. eHUBs may also benefit from greater visibility as hubs are easy to recognise and reliable spots to rent vehicles, thus avoiding concerns about shared vehicle availability. Nevertheless, various open questions remain, some of which are listed below.

For instance, little is known about the most effective combinations of different shared vehicle types. According to our definition, an eHUB consists of at least two shared electric vehicle types, yet different combinations of shared electric mobility options may be preferable in different environments. In inner-city environments, for instance, e-bikes and e-scooters may be the first choice, whereas in suburban or rural environments e-cargobikes and e-cars may be preferable. Future research therefore could focus on exploring which combinations work best for different spatial contexts with Stated Preferences experiments.

Furthermore, various additional functions of mobility hubs, ranging beyond the provision of shared electric vehicles, were not considered. For example, apart from their main function as a mobility hub, eHUBs also may serve as secure bicycle storage, private EV charging points, lockers for storing individual items, delivery pick-up points, and work or social spaces. The availability of such functions may be a decisive factor for using shared vehicles for some target groups and, consequently, should be investigated in future research.

5.3. Conclusions

While the evidence regarding the added value of mobility hubs with different types of shared modes remains limited, our research is among the first to provide a side-by-side comparison of the appeal of different shared (light) electric vehicle types to different target groups. More specifically, our findings suggest that different types of shared electric vehicles may be preferred and used by different demographic and transport user groups. Moreover, while our findings suggest that shared modes, such as e-bikes or e-scooters, may potentially replace trips already being made using sustainable modes, it is evident that increasing the diversity of shared electric vehicle fleets may benefit users, cities, and providers, alike.

5.4. Notes

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CRediT authorship contribution statement

Gustav Bösehans: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Visualization. **Margaret Bell:** Conceptualization, Investigation, Supervision. **Neil Thorpe:** Methodology, Investigation, Writing – review & editing. **Dilum Dissanayake:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

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

Acknowledgements

This work was supported by the EU-funded eHUBs project (Sponsor: INTERREG NWE, Project number: NWE 826). The sponsor neither had any direct involvement in the conduct of the research nor in the decision to submit the article for publication.

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