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Understanding factors influencing user retention in shared e-scooter schemes: A comparative study of the UK/EU and the US☆

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A R T I C L E I N F O

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A B S T R A C T

Shared e-scooters are increasingly recognised as a sustainable travel mode for tackling urban transportation challenges, including congestion and air pollution. Their early adoption in U.S. cities, followed by expansion across Europe and ongoing trials in the UK, underscores the need to understand key factors for the scheme's success and development, particularly regarding the acceptance and retention of existing users. This study adopts an explainable machine learning approach to predict and understand the likelihood of continued shared e-scooter usage among current users. It provides insights into the important factors influencing user retention, while also comparing the UK/EU and US contexts. The developed models exhibit high predictive accuracy and highlight the perceived utility and user-friendliness of e-scooters as key determinants influencing users' willingness for future use. The research sheds light on psychographic characteristics, emphasising the impact of green awareness and individual's values on users' retention, and how their importance may vary between the UK/EU and US users. The findings are useful for guiding future strategic development of shared e-scooter services in different geographic contexts.

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1. Introduction

Shared e-scooters are a part of the evolving landscape of urban public transport systems and micromobility services (Abduljabbar et al., 2021; Wang et al., 2023). Powered by rechargeable batteries, they are readily available for short-term rentals in particular locations within urban areas and are typically facilitated through a dedicated mobile app (Abduljabbar et al., 2021). By integrating such schemes into urban transportation networks, shared e-scooters could offer several benefits (Abduljabbar et al., 2021; Liao and Correia, 2022), including mitigating road traffic mitigation, solving the "last-mile" (distance between a transit hub and the traveller's ultimate destination) problem (Grant-Muller et al., 2023; Yang et al., 2019), contributing to lower carbon emissions (Felipe-Falgas et al., 2022), and improving users' mental health and well-being (Grant-Muller et al., 2023).

Cities in the United States were among the earliest to adopt shared e-scooter services, followed shortly thereafter by numerous regions across Europe. Shared e-scooters are also currently under government-approved trials in the UK, where their usefulness, potential advantages and drawbacks are being assessed (Grant-Muller et al., 2023). The schemes are now a common sight in many major cities worldwide, where multiple suppliers can operate concurrently within the same area (Grant-Muller et al., 2023). Comparing shared e-scooter schemes in different regions (e.g., the US and the UK/EU) is key to better understand user preferences and service provision dynamics influenced by distinct cultural norms, urban environments, and regulatory frameworks. Insights from such comparisons can help operators and policymakers tailor shared e-scooter services to meet the specific needs and expectations of local populations, leading to higher usage rates and satisfaction levels, and therefore more effective integration into the urban transportation systems.

For the shared e-scooters to continue to evolve as an attractive mode and consistently deliver a valuable mobility service, two important aspects must be taken into account: attracting new users and maintaining the engagement of current users (van Lierop et al., 2018). Current users may face some challenges or may have certain catalysts for continued usage; identifying and addressing these barriers and opportunities can help increase user retention and lead to the scheme's long-term success. Despite the critical role played by these two elements, existing literature appears to be skewed towards the former – primarily analysing differences between current users and potential new users, while the latter – understanding the retention and continued use among existing users – remains relatively less explored. Literature shows (Reck and Axhausen, 2021) that in some European cities (e.g., Zurich), around half of shared micro-mobility users are inactive or "dormant", and many people may have stopped using shared e-scooters. Reck and Axhausen (2021) highlight the importance of understanding the barriers and catalysts associated with users' retention and willingness to use e-scooters, although they acknowledge that a proportion of first-time users, e.g., tourists, may not have continued access to e-scooters in their home location.

Various factors, including sociodemographic and trip experience, have so far been explored in the literature to understand their impact on using shared e-scooters. More recently, a few studies (Blazanin et al., 2022) have started emphasizing the benefits of incorporating psychographic characteristics, such as time consciousness and green lifestyle, to better understand individuals' perceptions and behaviours regarding e-scooter usage. However, despite these few exceptions, the examination of psychographic variables remains relatively rare in existing literature. This study addresses this gap by incorporating highly relevant psychographic characteristics, alongside other important features (such as sociodemographic and trip/user experiences) in the modelling process. Specifically, drawing from Value–Belief–Norm (VBN) theory (Lind et al., 2015; López-Mosquera and Sánchez, 2012), we account for certain kinds of values and moral components, which have been found in prior empirical literature (see e.g., (Oreg and Katz-Gerro, 2006; Poortinga et al., 2004) to significantly enrich the understanding of why individuals engage in different behaviours, such as that examined here (i.e., shared e-scooter usage). Our approach offers a comprehensive understanding of shared e-scooter user retention, by collectively examining various attributes and their influence on individuals' willingness to continue the usage. In addition, this work compares the differences in the contexts of the US and UK/EU, where people have different levels of knowledge and experience in using shared e-scooters, as well as varying regulations associated with shared micromobility.

In this study, we employ a machine learning classification model (CatBoost) and an explanatory framework to answer the research question: what factors are of high importance in explaining user retention in the US and UK/EU contexts? We adopted machine learning models due to their advantages in modelling complex, non-linear and high-dimensional data (Chen and Xu, 2023; Cao and Tao, 2023). The explanatory framework can further provide deeper insights for the model into the contribution and impact of different variables and how they affect retention.

2. Literature review

Shared e-scooters emerged in the 2010 s, and the schemes have expanded globally, including the US, EU and Asian countries (Christoforou et al., 2021; Felipe-Falgas et al., 2022; Grant-Muller et al., 2023; Guo and Zhang, 2021; Hermawan and Le, 2022; Zhu et al., 2020). In addition to their potential environmental benefits and providing better accessibility in transportation (Badia and Jenelius, 2023), previous research in the UK context has indicated that shared e-scooters can enhance users' well-being and mental health (Grant-Muller et al., 2023) by providing access to local services, facilitating exposure to nature, reducing stress, and offering a sense of exercise. Individuals with protected characteristics or personal mobility issues (e.g., walking difficulty or no car access) are more likely to experience these well-being benefits (Grant-Muller et al., 2023). However, concerns remain about whether e-scooters are truly environmentally friendly, especially when considering their life-cycle impact (Félix et al., 2023; Schelte et al., 2021). Safety is another issue, as e-scooters can create conflicts with pedestrians, cyclists, and motorized vehicles. The decision to encourage shared e-scooters depends on various complex contextual factors, including, but not limited to, local population characteristics, transport infrastructure, safety, regulations and operation logistics (Schelte et al., 2021).

To better understand and promote the usage of shared e-scooters, literature has focused on investigating various factors that may impact the uptake and usage of this mode, particularly through questionnaire-based travel surveys (Wang et al., 2023). Christoforou et al. (2021) suggested that in the European context, the main motivations for trying shared e-scooters are the perceived playfulness, novelty, flexibility and time-efficient nature of this travel model. Almannaa et al. (2021) investigated people's propensity to use e-scooters, using data collected predominantly comprising (82 % of sample) of non-users' perspectives, hence yielding insights mostly relevant to potential newcomers rather than experienced users. In the study by Blazanin et al. (2022), 73.2 % of the sample consisted of individuals who had never used shared micromobility services (including bike sharing and e-scooters). As a result, insights from these studies largely reflect the views and expectations of non-users, offering a limited understanding of the experiences and future usage inclinations of current users.

Among existing shared e-scooter users, consumer innovativeness and green perceptions are significantly associated with usage (Flores and Jansson, 2021) in European countries. Similarly, Blazanin et al. (2022) suggest that some psychographic factors (time consciousness and green lifestyle) can impact the adoption and use frequency of shared e-scooters in the US.

In addition to using survey data (Flores and Jansson, 2021) to understand user retention, trip record data were also used in literature to identify the key factors that affect shared e-scooter use, normally by exploring how the local (e.g., around trip origins or destinations) built environment, land use, and sociodemographic characteristics are associated with the trip amount (Bai and Jiao, 2020; Caspi et al., 2020; Guo and Zhang, 2021). In the US context, a higher number of e-scooter trips in an area is associated with higher population density, higher educational attainment, better street connectivity, compact land use, and cycling infrastructure.

Building on this foundation, the exploration of user retention and trip patterns through statistical models has paved the way for more sophisticated analyses. Statistical models (Flores and Jansson, 2021) are used in literature to understand different factors (e.g., age, gender) and their impact on shared e-scooter usage. Machine learning models may also be applied to obtain related insights, especially due to their advantages in dealing with high-dimensional data, modelling non-linear relationships, and performing well in classification and regression tasks (Chen and Xu, 2023; Cao and Tao, 2023). For example, survey data about e-scooter users can be high dimensional and contain comprehensive variables across different domains, such as various sociodemographic features, psychographic characteristics, and travel behaviours, with fine granularity details describing different levels or categories on each feature. Recent developments in explainable machine learning models and frameworks are emerging as new toolkits for understanding the impacts of user's features on travel behaviours and related perceptions (Kieu et al., 2023). Many early machine learning models were criticised as black-box models, offering little to no interpretability on how the results or decisions were obtained (Rudin, 2019). In contrast, explainable machine learning focuses on making the model processes understandable and interpretable to humans, for example, to provide insights into why a model makes a particular prediction, which features are most influential, and how changes in input data may affect the model's output. Among different explainable machine learning models, Gradient Boosting models (e.g., CatBoost) and SHAP (SHapley Additive exPlanations) (Kaur et al., 2020) have been adopted for transportation analysis, such as understanding transport accidents (Hasan et al., 2023), rail transfer behaviours (Mao et al., 2023), decisions on replacing an old vehicle in the household (Jin et al., 2022), and acceptability and attitude on new transport policy (Kieu et al., 2023). However, these models have been relatively underutilised in empirical studies aimed at uncovering the nuanced factors associated with shared e-scooter usage. Among the few relevant micromobility studies, SHAP was applied to understand the impact of temporal factors, meteorological conditions, and built environments on the use of shared bikes and e-scooters (Ren et al., 2023).

Overall, data-driven insights derived from machine learning models and SHAP have the potential for understanding different factors and their impact on people's travel (including shared e-scooters) behaviours and perceptions. Expanding these models to incorporate a broader range of psychographic factors and conducting comparative studies across different contexts (e.g., the UK/EU and the US) would provide robust, quantifiable evidence to inform more effective policy and service design.

3. Data and methods

3.1. Dataset

The data for this study were collected through a travel survey between September 2021 and December 2022. The survey was distributed as an e-survey with the collaboration of multiple e-scooter service providers, namely Bird, Helbiz, Lime, Lyft, Razor and Spin. However, the survey questions were developed independently by the research team and driven by research questions. The e-survey questions were designed to reflect underlying behavioural theories, including the VBN theory (Lind et al., 2015; López-Mosquera and Sánchez, 2012) and marketing models, alongside questions capturing demographic characteristics, trip characteristics, access to transport and other aspects (Davis, 1989; Han, 2015; Haustein et al., 2018; Leonidou and Skarmeas, 2017; Sandy et al., 2017). The survey had ethical approvals from the University of Leeds and University of California, Davis ethics committees and was administered electronically through the Qualtrics platform.

The e-scooter providers contacted those individuals in their existing customer database who had agreed to receive communications related to services or research with a link to the survey. All participants were entered into a prize draw for e-shopping vouchers to the value of £50 or equivalent. The UK/EU survey primarily focused on cities in the UK, with further participation from other European countries (details in Table 1). The US survey was conducted in multiple regions, including Portland and Washington, DC, and it allowed responses from both residents and those visiting the city. Post-data cleaning and pre-processing were used to eliminate invalid responses and impute a small proportion of missing values; therefore, a set of 968 responses in the UK/EU and 1593 in the US were compiled to form the foundation of this study.

Table 1 illustrates the use frequency and geographical distribution of participants, including three cities in the UK and several countries across Europe, as well as two cities in the US. It is important to note that responses from other regions in the US were excluded from the final dataset due to small sample sizes, which prevented meaningful analysis. In the UK/EU region, 8.6 % of participants reported that they had only used the service once so far, and more than half of the UK/EU respondents used the service at least once a month or with higher frequencies. Most respondents (81.5 %) are from the three UK cities, with the remaining respondents in Finland, Germany, Norway and Sweden. In the US region, "More than once, but not every month" is the most common response (39.5 %), followed by "At least once a month" (24.8 %), while 12.5 % reported using "Only once so far." Most (69.4 %) of the US respondents are from Washington, DC.

In the survey, the questions were tailored with varied response types according to the nature of the query (see Table 2). For instance, sociodemographic questions offered categorical options such as diverse age groups or genders. In contrast, queries about first-user experience and opinions, and psychographic characteristics involved responses on an ordered five-point Likert scale, for example: Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, and Strongly agree.

For the question regarding the propensity to use e-scooters in the future, the five-points were ordered: Very unlikely, Unlikely, Undecided, Likely, and Very likely. In addition to sociodemographic attributes, a number of questions regarding psychographic characteristics (individual's values) were also included in our survey, with the following format: "How much do you agree with each of the following statements – I feel … is important". The questions about psychographic characteristics account for certain kinds of values and moral components and are drawn from VBN theory. Grounded in social psychology, VBN extends

Table 1
Self-reported use frequency and place.

Region	Variable	Categories	n	%
UK/EU	Use frequency	Only once so far	83	8.6
		More than once, but not every month	309	31.9
		At least once a month	309	31.9
		More than once a week	267	27.6
	City/Country	Canterbury, UK	13	1.3
		Essex, UK	653	67.5
		Milton Keynes, UK	123	12.7
		Finland	45	4.6
		Germany	48	5.0
		Norway	26	2.7
		Sweden	60	6.2
US	Use Frequency	Only once so far	200	12.5
		More than once, but not every month	629	39.5
		At least once a month	395	24.8
		More than once a week	369	23.2
	City	Portland	487	30.6
		Washington, DC	1106	69.4

Table 2
Key Questions and Attributes in the Survey.

Domain	Question
Sociodemographic Characteristics	Age
	Gender
	Educational attainment
	Job/Economic activity
	Annual household income
	Vehicle ownership
Psychographic characteristics (Individual's values)	Having wealth or being in authority in my work role
	Be successful and achieve a high level in my work role
	Enjoyment in life, having a few luxuries, and getting the things I want
	Life is exciting, challenging and varied
	Having the freedom to choose my goals, to be creative, and to be independent
	Honesty, forgiveness, loyalty, and taking responsibility
	Humbleness, respect for tradition and devotion
	Self-disciplined, honor my elders and to be polite
	A world at peace, the beauty of nature and equality
	Reduce my impact on the environment
	Feel a moral obligation to use e-scooters for environmental reasons
	Feel personally obliged to tackle traffic related problems by choosing e-scooters in future
First-time shared e-scooter user experiences	Allowed me to complete my trip more quickly
	Made my trip easier
	Easier to take an e-scooter than have a long or difficult walk
	It seemed easy to adjust the way I usually travel by using an e-scooter
	The e-scooter was easy to ride
	My interaction with the e-scooter App was clear and easy to understand
	The e-scooter was flexible in interacting with other road users
	I saw a few people trying e-scooters and wanted to try e-scooters too
	A friend, colleague, or family member encouraged me to try it

the norm activation framework (Schwartz, 1977) and postulates that individuals' values, such as the sense of obligation (i.e., personal norm), are key determinants of their decision to engage in pro-environmental behaviours (Skarmeas et al., 2020; Stern, 2000). User experiences are also important parts of the questionnaire (Table 2), especially regarding user's first e-scooter trip and how they feel about it in different aspects.

This dataset is unique in that it includes only individuals who have had at least one experience using shared e-scooters. As such, every respondent possesses a certain level of familiarity with the scheme. This feature sets our research apart from many studies in the literature (Almannaa et al., 2021; Blazanin et al., 2022), where most respondents are typically non-users. In addition, it asks relatively consistent questions for both the UK/EU and US shared e-scooter users, with only necessary amendments for local context, such as educational qualifications, which facilitate comparison between the two contexts.

3.2. Classification model with CatBoost

To understand a user's retention decision with shared e-scooters, we first constructed a classification model with machine learning. A machine learning model was built to predict the binary outcome of an individual's willingness to use e-scooters in the future, i.e. whether a person is "willing" (combining "Very likely" and "Likely") or "not willing" (including "Very unlikely", "Unlikely" and "Undecided") to use e-scooters in the future (Kieu et al., 2023). The decision to aggregate these categories into a binary outcome was driven primarily by the limited sample size, particularly in the "Very unlikely" and "Unlikely" responses. Additionally, this binary classification was necessary for this specific part of the study, which required a simplified outcome variable for effective modelling. It is worth noting that the collected data has been used for various other modelling and analysis studies, which may have utilized different categorizations. The inputs (independent variables) of the model consist of people's sociodemographic attributes, psychographic characteristics, and relevant first-time shared e-scooter user experiences (Table 2).

In this section, we discuss the relative merits of machine learning (ML) and justify the specific approach used in our study. Since the input data is high dimensional and covers a wide range of characteristics (Table 2**),** this study adopted an explainable machine learning approach. Among different machine learning models, gradient boosting trees is a powerful algorithm to develop a predictive model. The central concept of boosting is constructing a strong model from an ensemble of weak models in series, with each model fitted to the residuals of the previous models (Kieu et al., 2023). This is different from bagging methods (e.g. Random Forest) (Altman and Krzywinski, 2017), which only deal with high variability in the data. Boosting not only reduces this variability, but also manages the balance between model complexity and accuracy, making it generally a stronger tool (Kieu et al., 2023). Among various implementations of gradient boosting trees, CatBoost can outperform some cutting-edge gradient boosted decision trees (GBDTs), such as XGBoost (Yang et al., 2020) and LightGBM (Dorogush et al., 2018). Notably, CatBoost constructs balanced, symmetric trees, where previous tree leaves are divided using the same modelling conditions. This particular tree architecture aids in managing overfitting due to its inherent regularisation properties. Furthermore, CatBoost employs the ordered boosting strategy, a permutation-based method that trains the model on a specific data subset while determining residuals on another. This strategy can mitigate target leakage and overfitting, thereby enabling CatBoost to better handle small or noisy datasets than traditional boosting algorithms (Dorogush et al., 2018).

An important feature of CatBoost and GBDTs, compared to traditional multiple regression, is their ability to fit a non-linear relationship between a dependent variable and independent variables. The model can also present feature importance scores and ranks to provide a clearer understanding of the variables' impact and their importance. CatBoost's iterative boosting framework and native handling of non-linearities can help uncover subtle signals where feature variability is somewhat limited. Unlike traditional linear models, which may miss weak patterns, CatBoost builds trees in successive steps—each focusing on the errors of the previous iteration—and uses robust regularization to prevent overfitting. This combination often allows CatBoost to tease out small but meaningful sources of variation more effectively, especially when compared with simpler, more rigid approaches.

In this study, the survey datasets were randomly split into training (80 %) and testing (20 %) sets, respectively, for both the UK/EU and US data. Grid search and k-fold cross-validation were utilised for hyperparameter tuning based on the training set of the two regions. The hyperparameter grid for tuning is shown in Table 3. The models' performances are finally evaluated with the two testing sets, and the results for both the UK/EU and US data are reported in the results section.

3.3. Feature importance analysis

An important part of understanding the constructed classification model (section 3.2) is to investigate the impacts and contributions of

Table 3
Hyperparameter tunning grid.

Hyperparameter	Values
Learning rate	0.001, 0.01, 0.05, 0.1, 0.3
Iterations	100, 150, 200, 250, 300, 400, 500
Depth	3, 6, 9

each variable (Kieu et al., 2023; Yang et al., 2020). Feature importance analysis measures the extent to which each variable contributes to the precision of the classification model's predictions. It indicates the degree to which each variable assists in predicting the future propensity to use shared e-scooters. Feature importance analysis is also an important step in the development of classification models (Kieu et al., 2023; Yang et al., 2020). In the process of simplifying while building robust machine learning classification models, variables with low importance are typically excluded. This process begins with the construction of an initial model that includes numerous variables. Following this, importance scores are generated for this initial model. In the next stage, variables are iteratively removed, starting from the least important ones, as long as the model's accuracy remains unaffected (Kieu et al., 2023). The finalised model, thus, represents a simple yet robust construct. In addition to the above feature-selecting process, each model input variable is also examined in terms of statistical distribution and correlations, before being used in the model. To retain consistency in the UK/EU model and US models, the same group of variables are utilised in the final model, and are listed in Table 2 as the key questions and attributes. If one variable, in either dataset (the UK/EU and US), does not pass the statistical check, or has a multicolinearity issue, or appears as not important, then it will be dropped in both models.

Once the classification model is constructed, it is trained on the UK/EU and US training datasets separately to predict a specific person's future willingness to use shared e-scooter service. Moreover, it is beneficial to understand how each individual's sociodemographic, psychographic characteristics and e-scooter user experiences may be associated with their willingness and retention. To fulfil this, SHAP (Lundberg et al., 2020; Lundberg and Lee, 2017; Štrumbelj and Kononenko, 2014) is employed in this study to interpret the built CatBoost classification models and how different variables may impact the outcome. SHAP is based on the concept of Shapley values (Štrumbelj and Kononenko, 2014) from cooperative game theory, which provides a way to fairly distribute the "contribution" of each feature in a prediction among its individual components. Furthermore, SHAP can evaluate the influence that various distributions or values of each variable have on the model's output. For instance, in a binary classification task, SHAP offers insights into how particular values of a variable can impact the prediction, determining whether it leans towards a positive (willing) or negative outcome (not willing). By considering different distributions or values, SHAP facilitates a deeper understanding of the relationships between input variables and the resultant predictions, enabling a more comprehensive interpretation of the model's behaviour (Kieu et al., 2023).

SHAP has been successfully applied in various transport studies, for example, on survey data to understand people's perceptions of transport policy (Kieu et al., 2023), mobility behaviours (Hak Lee et al., 2021), and the difference among varying groups of people and contexts (Hasan et al., 2023; Jin et al., 2022; Kieu et al., 2023; Mao et al., 2023; Ren et al., 2023).

4. Results

4.1. Sociodemographic characteristics

The dataset includes multiple sociodemographic variables, including age, gender, educational attainment, economic activity, household car ownership, and annual household income. Among the respondents

Table 4
Sociodemographic attributes of respondents.

Variable	UK			US		
	Categories	*n*	%	Categories	*n*	%
Age	18–24	211	21.8	18–24	323	20.3
	25–34	302	31.2	25–34	636	39.9
	35–54	392	40.5	35–54	540	33.9
	55–64	40	4.1	55–64	65	4.1
	65+	11	1.2	65+	10	0.6
	Prefer not to say	12	1.2	Prefer not to say	19	1.2
Gender	Male	674	69.6	Male	841	52.8
	Female	285	29.4	Female	689	43.2
	Prefer to self-describe	9	1.0	Prefer to self-describe	63	4.00
Educational attainment	Other	20	2.1	Other	98	6.2
	Secondary school	187	19.3	High school	210	13.2
	Higher (e.g., technical college)	294	30.4	Some college/technical school	311	19.5
	University (first degree)	303	31.3	Bachelor's degree(s)	569	35.7
	Postgraduate degree	164	16.9	Postgraduate degree	405	25.4
Economic activity	Active	840	86.8	Active	1350	84.8
	Inactive	128	13.2	Inactive	242	15.2
Car ownership	Have	772	79.8	Have	1154	72.4
	Do not have	196	20.2	Do not have	439	27.6
Annual household income	Less than £25,000	252	26.0	Less than $25,000 (≈£19,750)	273	17.1
	£25,000–49,999	279	28.8	$25,000–49,999 (≈£19,750–39,500)	283	17.8
	£50,000–74,999	191	19.8	$50,000–74,999 (≈£39,500–59,246)	260	16.3
	£75,000–99,999	102	10.5	$75,000–99,999 (≈£59,246–79,000)	205	12.9
	£100,000–149,999	71	7.4	$100,000–149,999 (≈£79,000–118,500)	258	16.2
	£150,000 or more	73	7.5	$150,000 or more (≈£118500 or more)	314	19.7

(Table 4) in the UK/EU, the age group between 35 and 54 constitutes the largest segment (40.5 %), followed by the 25–34 age group (31.2 %); this is different to the US cohort, as there is larger proportion (39.9 %) aged between 25 and 34, higher than the share (33.9 %) of age group 35–54. In the UK/EU, male users dominate the sample, representing 69.6 % of the participants; the gender gap is smaller in the US, showing 52.8 % of male participants. Regarding educational attainment, a greater proportion of US respondents have obtained higher education or higher, compared to the UK/EU respondents. The majority of users (both above 84 %) are economically active, and the share of economically inactive groups (including students, retired, not in paid work, etc.) is small. In both regions, more than 70 % of respondents have car access in their households. Lastly, the analysis of annual household income reveals that aggregately, 45.2 % of respondents in the UK/EU have an annual household income of more than £50,000, while the UK median value is around £34,000. For the US cohort, there is a high proportion (19.7 %) of respondents with very high household income ($150,000 or more, approximately £118500 or more), and aggregately 48.8 % with income more than $75,000 (approximately £59,246).

In the machine learning model developed, income is converted to a ratio with local (regional or city level, e.g., Washington DC and Portland) median household income (in the year 2021) as the denominator, and the mid-value in each income bracket as the numerator. It should be noted that there are still different approaches to taxation and social provision between the two countries, which means household income levels are not directly comparable, even considering local scales.

Despite the difference between the UK/EU and US respondents, the sociodemographic characteristics of the respondents overall align with findings from other shared e-scooter studies (Blazanin et al., 2022; Christoforou et al., 2021; Grant-Muller et al., 2023) and real-world users of similar schemes. It is important to mention, however, that published evidence for direct comparison is limited, especially from the UK. Similar micromobility studies (Blazanin et al., 2022; Christoforou et al., 2021; Grant-Muller et al., 2023) have also indicated that users tend to be young, well-educated, and financially well-off, with a higher representation of males.

4.2. Willingness to use shared e-scooters in the future

The survey provides insights into the propensity of future shared e-scooter usage among current users. Fig. 1 shows a high level of willingness among the respondents to continue their usage, with 72 % and 74 % "Very likely" to use e-scooters in the future, in the US and UK/EU regions, respectively. Additionally, two regions have similar proportions (20.8 % and 20.9 %) of respondents choosing "Likely", and their positive opinion shows an opportunity for scheme expansion and increased user engagement. These responses may be relevant to a favourable perception of the benefits and convenience associated with e-scooter usage, as introduced in the next section.

From Fig. 1, there are smaller segments of respondents who were Undecided (4 % US and 3 % UK/EU), Unlikely (1.8 % and 1.2 %), or Very unlikely (1.4 % and 0.9 %) to use shared e-scooters in the future. The Undecided group hadn't expressed a positive inclination to use the shared e-scooters again in the future; therefore, these three groups are combined into a single 'Not Willing' (or 'Negative') group in the binary classification model.

4.3. User experiences

In the survey, a number of questions were posed addressing individuals' user experiences of their first shared e-scooter travel. The survey results are presented in Fig. 2 for three key aspects: (1) Ease of use (labelled as "Easy"), (2) Utility ("Useful"), and (3) Substitute and adjust modes of transport ("Mode").

High proportions of respondents expressed favourable opinions of their first shared e-scooter user experience. Regarding user-friendliness, aggregately around 90 % of responses in both regions consider e-scooter vehicles easy to ride. Considering the associated App (shared e-scooter apps), 47.7 % of respondents strongly agreed it is user-friendly and intuitive in the UK/EU, and the figure is higher than in the US (41.2 %). It should be noted that the operators in the survey in the two regions are different; hence different types of Apps and e-scooters are used.

In both regions, more than half of respondents strongly agree that shared e-scooters are useful and make their trips easier; around 70 % of the respondents emphasised (Strongly agree) the speed (more quickly) advantage offered by e-scooters. A higher proportion (66.6 %) of US respondents strongly agree a shared e-scooter is a preferable alternative to a lengthy walk, compared to the UK/EU (57.5 %). In the two regions, the perception related to adjusting the travel mode reached a similar pattern across different responses, with more than half of respondents holding a positive opinion (somewhat agree or strongly agree).

4.4. Psychographic characteristics

Questions regarding psychographic (Individual's values) characteristics were also asked as a part of the survey. Here, questions related to four domains were investigated and reported, namely their view on (1) "Achievement, Wealth and Power" (AWP); (2) "Environmental and Social Consciousness" (ESC); (3) "Enjoyment, Excitement and Freedom" (EEF); and (4) "Tradition and Integrity" (TI). The results are shown in Figs. 3 and 4.

Over half of respondents consider AWP important, and the US respondents tend to agree more on this than the UK/EU cohort. For example, 34.3 % of US participants emphasise (strongly agree) the importance of achieving success in their professional lives, higher than the figure (24.6 %) in the UK/EU.

Regarding ESC (Fig. 3), US respondents are more likely to agree on protecting the environment and the world and consider the beauty of nature important. However, the stated green awareness is not effectively lead to higher adoption of shared e-scooter travel, since a lower ratio (aggregately 30.4 %) of US respondents feel a moral obligation to use e-scooter for environmental reasons, compared to the 34.4 % in the UK/

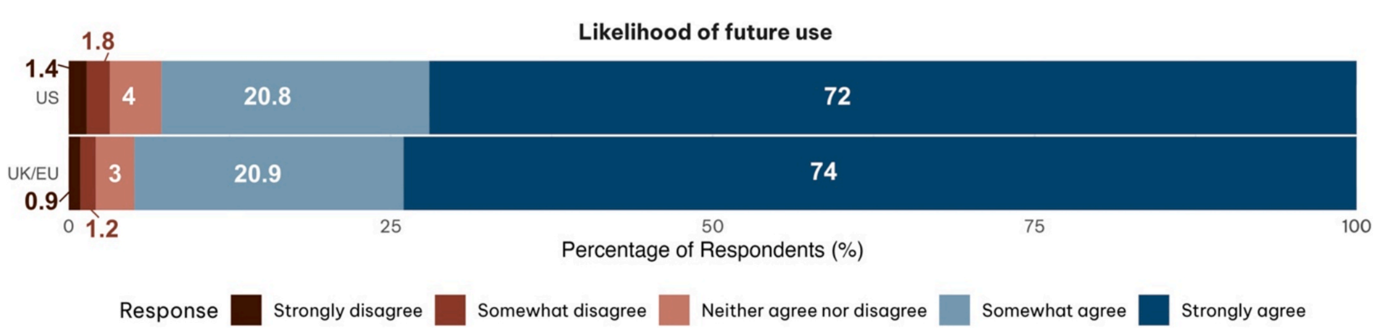

Fig. 1. Likelihood of Future Use of Shared E-scooters.

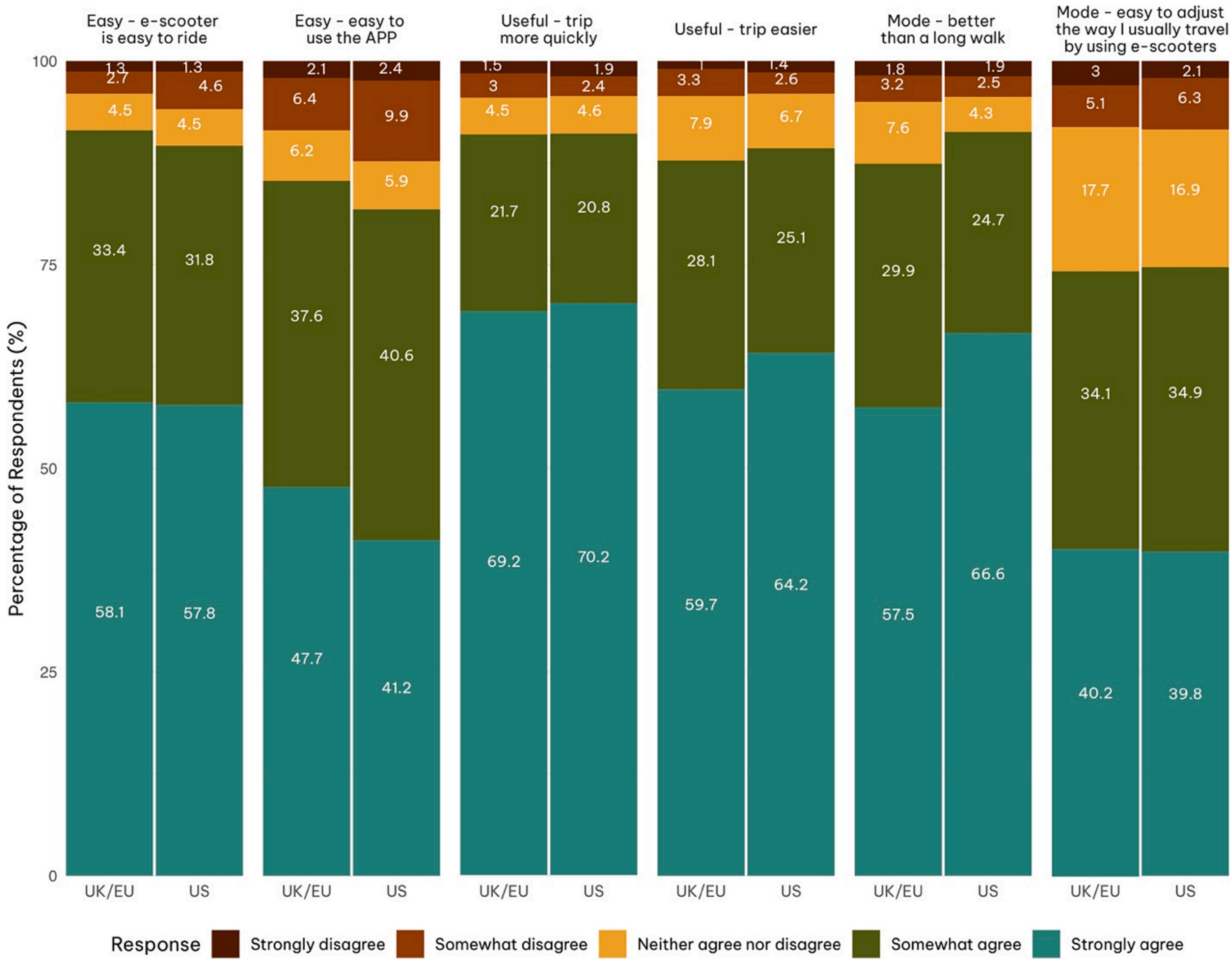

Fig. 2. Perception on Users' First E-scooter Travel.

EU. It is likely that in the US context, using shared e-scooters is less perceived as an effective way to tackle the issues related to the environment and transportation systems, compared to in the UK/EU.

The majority of respondents in both regions consider EEF important (Fig. 4). In both regions, between 75.8 % and 88.3 % of respondents somewhat agree or strongly agree that enjoying life, experiencing excitement, and having freedom are important aspects. The US cohort shows a consistent pattern of higher agreement than respondents in the UK/EU.

In the TI domain (Fig. 4), there is a considerable level (all greater than 50 %) of agreement among the respondents, particularly regarding honesty, forgiveness, loyalty and taking responsibility. Humbleness, respect for tradition and devotion received relatively the lowest agreement. Respondents from the UK/EU are more likely to strongly agree on self-discipline, honouring elders and being polite.

4.5. *Classification model performance*

Once the CatBoost binary classification models were constructed and trained using the training sets (80 % of the sample), their accuracies were evaluated using the testing sets (20 %). Several model performance metrics (Table 5) reveal that the models accurately predict the test sets, and the two models reached comparable performance in the UK/EU and US, both with an accuracy of around 83.7 %. The Recall (True Positive Rate) indicates that the model successfully detected 83.71 % and 83.90 % of individuals willing to use e-scooters in the future. Additionally, the models exhibit specificity metrics both greater than 80 %, reflecting their ability to correctly identify negative instances (those who might leave the shared e-scooter scheme). With Positive Predictive Values (PPV), or precision, equal to or higher than 98 %, the models demonstrate a high proportion of accurate positive classifications. The F-measure, which combines and balances precision and recall, yields values of around 90 % for the two models. Overall, the developed models reached satisfactory and comparable performances in the binary classification tasks, accurately predicting individuals' stated willingness to use e-scooters in the future.

4.6. *Feature importance*

With satisfactory performances from the classification models, it is possible to evaluate the importance of each feature (variable). This will help to gain insights into how each contributed to and impacted, predicting future willingness to use.

SHAP is used to obtain the importance score of features, and Table 6 provides a comprehensive breakdown of feature importance, including Relative Importance (RI) and Importance Rank. RI is determined by dividing the individual feature importance by the sum of all importance scores and converting it into percentage values. The RI and Rank are

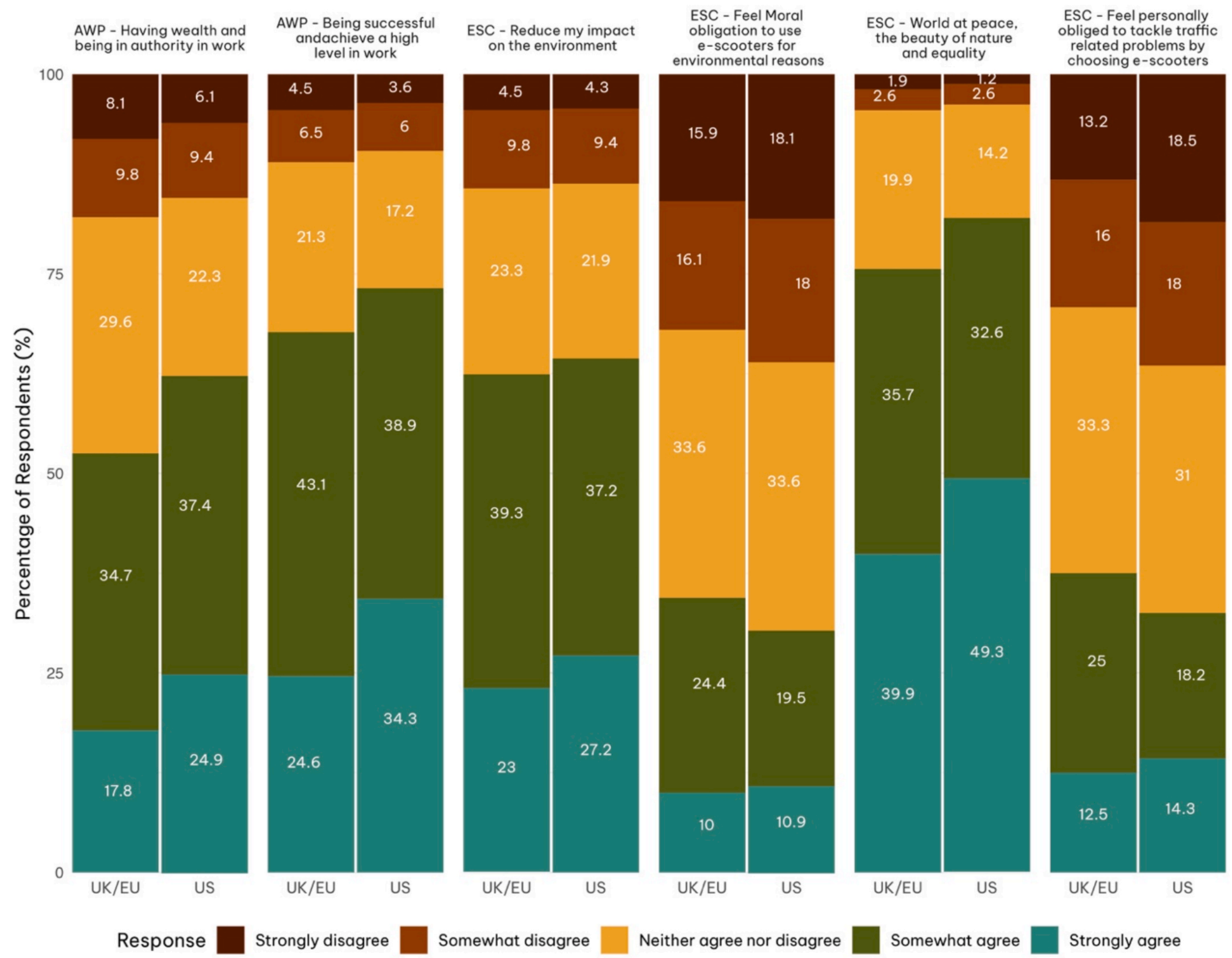

Fig. 3. Psychographic characteristics of AWP and ESC.

reported for the UK/EU and US, respectively; hence, it is possible to compare the difference of feature importance in the two regions. In the Appendix, Tables A1 and A2 present feature importance for the two regions in descending order of importance. Although similar to Table 6, the Appendix more intuitively illustrates feature importance for each region.

From Table 6, the collective contribution (sum of RI) of user experiences (UE) factors to predict future willingness usage is the highest, reaching 68.65 % and 60.76 %, respectively, for the UK/EU and US. Psychographic (PG) characteristics accounted for 25.48 % and 30.70 %, while sociodemographic (SCD) attributes contributed to 5.89 % and 8.52 %. Educational attainment and car ownership have higher impacts on user retention in the US than in the UK/EU. The difference in the importance of car ownership could reflect the modes that shared e-scooters are replacing and facilitating in different areas (Wang et al., 2023). For example, replacing walking trips and connecting public transport (e.g., bus) trips versus replacing private car trips can lead to variations. The former is less relevant to car ownership and, thus, less important. Household income obtained similar ranks, at 20th and 19th, respectively.

In the psychographic domain, the variable "Enjoyment in life, having a few luxuries, and getting the things I want" was ranked 6th in the US model with RI at 6.5 %, but it has low importance in the UK/EU, only 0.88 % and ranked 24th. Similarly, the psychographic characteristics of "Having wealth or being in authority in my work role is important to me." is more important for keeping using shared e-scooters in the US. "Feel a moral obligation to use e-scooters for environmental reasons" is more important in the UK/EU for user retention, ranking 8th, compared to 13th in the US.

There are three factors related to green awareness: (1) Reduce my impact on the environment, (2) A world at peace, the beauty of nature and equality, (3) Feel a moral obligation to use e-scooters for environmental reasons. Collectively, these green awareness factors contributed to a 7.31 % Relative Importance (RI) in the prediction model in the UK/EU, and 5.70 % in the US, emphasising the contribution of individuals' environmental protection perspectives.

"Life is exciting, challenging and varied" is an important feature (10th) for predicting retention in the US, but it falls behind in the UK/EU model and only ranks 22nd. On the contrary, "Being successful", "Humbleness, respect for tradition and devotion" and "Self-disciplined, honour my elders and to be polite" are relatively important features in the UK/EU (6th, 13th, 11th), but less helpful for predicting future usage in the US (15th, 27th, 24th).

Finally, under the shared e-scooter user experience domain, some features ranked high in both models and regions, for example "made my trip easier" and "user friendly app". Shared e-scooter is "easy to ride" and helps make a "quicker trip" score high rank in both regions. These underline the importance of e-scooters in facilitating efficient, user-

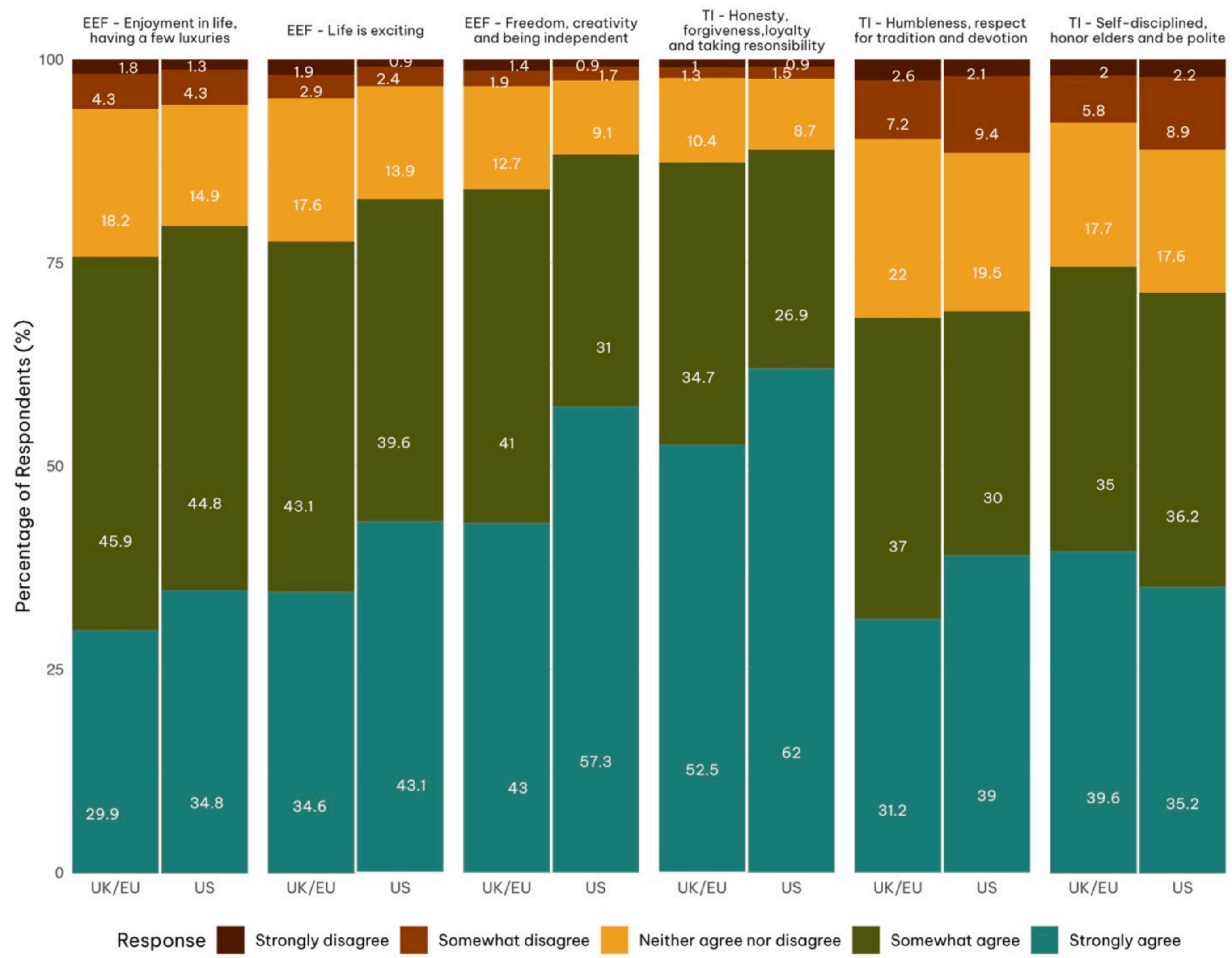

Fig. 4. Psychographic characteristics on EEF and TI.

Table 5
Classification models' performances.

Metric	UK/EU	US
Accuracy	83.68 %	83.70 %
Recall	83.71 %	83.90 %
Specificity	83.33 %	81.48 %
PPV	98.68 %	98.00 %
F-measure	90.58 %	90.41 %

friendly urban mobility, suggesting that users highly value the utility and ease of the mode. However, regional differences are notable in the most important variables. While "better than walking" reached the highest in the UK/EU, the US model shows the "easy to adjust the way I usually travel by using an e-scooter" is more important than replacing walking. Both of the two features are relevant to mode change/ replacement. The UK/EU respondents may consider replacing long walking trips as particularly important for continue using shared e-scooter services; while in the US, there is a higher emphasis on the adaptability of e-scooters to existing routines and transportation networks, for example, by supporting first/last-mile trips as a part of other public transport trips.

In summary, Table 6 presents a comprehensive interpretation of the relative importance of various variables influencing current users' willingness to use e-scooters in the future, as determined by CatBoost and SHAP. The next section uses SHAP analysis further to understand the impact of different features in detail.

4.7. SHAP value interpretation

SHAP analysis is a powerful tool that can reveal complex relationships between input features and predictions. Figs. 5 and 6, the SHAP summary plots (top 15 variables) for the UK/EU and US models, display individual SHAP values for each data record. These values are depicted on the x-axis, with dummy/binary variables shown in two colours and ordered variables represented by a spectrum of colours (ranging from blue to red) based on their values (e.g., from "Strongly disagree" to "Strongly agree"). Positive SHAP values (x-axis) for each respondent and variable contribute to a positive outcome, indicating a willingness to use shared e-scooters in the future. Conversely, when the SHAP value is negative, it implies the feature has a negative impact on the outcome, indicating an unwillingness to keep using the service. The variables on the y-axis are ordered by their importance rank (Table 6) in the UK/EU and US models, respectively.

Insights can be derived from Figs. 5 and 6 regarding the relationship between different feature values and the outcome of interest (i.e. willingness to use e-scooters). In general, individuals who have had a positive first experience with shared e-scooters and perceive them as

Table 6
Feature importance for willingness of future use.

Domain	Variable Definition	UK/EU		US	
		RI (%)	Rank	RI (%)	Rank
Sociodemographic Characteristics (SCD)	Age	1.85	16	1.10	23
	Gender	0.65	26	0.70	24
	Educational attainment	1.03	23	2.64	11
	Economic activity	0.23	27	0.68	26
	Household income	1.40	20	1.49	19
	Car ownership	0.73	25	1.91	17
Psychographic characteristics (PG)	Reduce my impact on the environment	1.72	17	1.20	22
	Honesty, forgiveness, loyalty, and taking responsibility	1.94	14	1.67	18
	A world at peace, the beauty of nature and equality	2.19	12	2.24	14
	Feel a moral obligation to use e-scooters for environmental reasons	3.40	8	2.26	13
	Having the freedom to choose my goals, to be creative, and to be independent	2.26	10	4.40	8
	Life is exciting, challenging and varied	1.14	22	2.88	10
	Feel personally obliged to tackle traffic related problems by choosing e-scooters in future	1.87	15	1.42	20
	Be successful and achieve a high level in my work role	4.49	6	2.19	15
	Humbleness, respect for tradition and devotion	2.10	13	0.56	27
	Self-disciplined, honor my elders and to be polite	2.22	11	0.78	24
	Having wealth or being in authority in my work role is important to me.	1.27	21	4.60	7
	Enjoyment in life, having a few luxuries, and getting the things I want	0.88	24	6.50	6
First-time shared e-scooter user experiences (UE)	Allowed me to complete my trip more quickly	8.93	4	8.43	4
	Made my trip easier	12.39	2	8.68	3
	Easier to take an e-scooter than have a long or difficult walk	21.17	1	2.51	12
	It seemed easy to adjust the way I usually travel by using an e-scooter	4.38	7	13.28	2
	The e-scooter was easy to ride	4.74	5	7.22	5
	My interaction with the e-scooter app was clear and easy to understand	11.44	3	14.30	1
	The e-scooter was flexible in interacting with other road users	2.41	9	1.26	21
	I saw a few people trying e-scooters and wanted to try e-scooters too	1.69	18	3.13	9
	A friend, colleague, or family member encouraged me to try it	1.50	19	1.95	16

making the trip easier and/or quicker are more likely to continue using them. These variables are characterised by high positive SHAP values with high agreement levels, represented by red dots in Figs. 5 and 6. Specifically, favourable perceptions regarding the ease of using the App and riding e-scooters are linked with better user retention in both the UK/EU and US. Furthermore, most features related to higher environment and social responsibility exhibit positive SHAP values, showing higher agreement dots with red colour. This suggests a positive association between these factors and a greater inclination to use e-scooters in the future.

A dependence plot is a scatter plot of the SHAP value vs feature value for a single feature. This method of visualisation is especially beneficial when examining features that may exhibit a non-linear association with the target variable. Figs. 7 and 8 show the SHAP dependence plots on age and easy App. The x-axis represents the categories of the variables, while the y-axis shows the SHAP value, each dot is a sample in the data. Those with SHAP values greater than 0 (above the dashed line) indicate that the feature at this data point has a positive effect on user retention, while smaller than 0 (below the dashed line) implies a negative impact.

Fig. 7 shows that the group with the highest positive impact is the youngest group aged 18–24 in the UK. In the older age band (above 65 years), the negative impact is evident and consistent in both regions, as indicated by the spread of points mostly below the zero line. A similar trend is observed in the US model, where younger ages tend to have larger and more positive SHAP values compared to older ages. This suggests that older people are more likely to become inactive in shared e-scooter schemes.

While US e-scooter users who consider the App to be easy to use in general (Somewhat agree and Strongly agree) lead to higher positive SHAP value (Fig. 8), the effect is different in the UK as the Strongly agree group is associated with positive SHAP value, while the Somewhat agree may have a negative impact. This indicates that in the UK, as shared e-scooter is a relatively new form of transport, users may lack confidence and have lower tolerance for the ease of using the shared e-scooter App. However, this might also be due to the use of different Apps and shared e-scooter schemes across various regions. Additionally, the Apps may have distinct features or compromises to comply with the privacy and data governance rules specific to each region.

Fig. 9 shows the similar effect of the trip experience “Made my trip easier”. The UK/EU and US models show a consistent pattern on SHAP values, as the Strongly agree group shows a positive impact on the model’s prediction with SHAP values above zero, while a small portion of the Somewhat agree group are above the zero line. The remaining groups all show negative SHAP values, hence leading to unwillingness to use shared e-scooters. The finding highlights service efficacy’s importance in influencing retention across cultures and contexts.

Overall, the SHAP analysis provides deeper insights into how various variables and their values/categories may impact individuals’ inclination to use shared e-scooters in the future. Additionally, it shows regional differences or similarities among varying variables and factors, which could inform targeted strategies for market-specific improvements and communication campaigns.

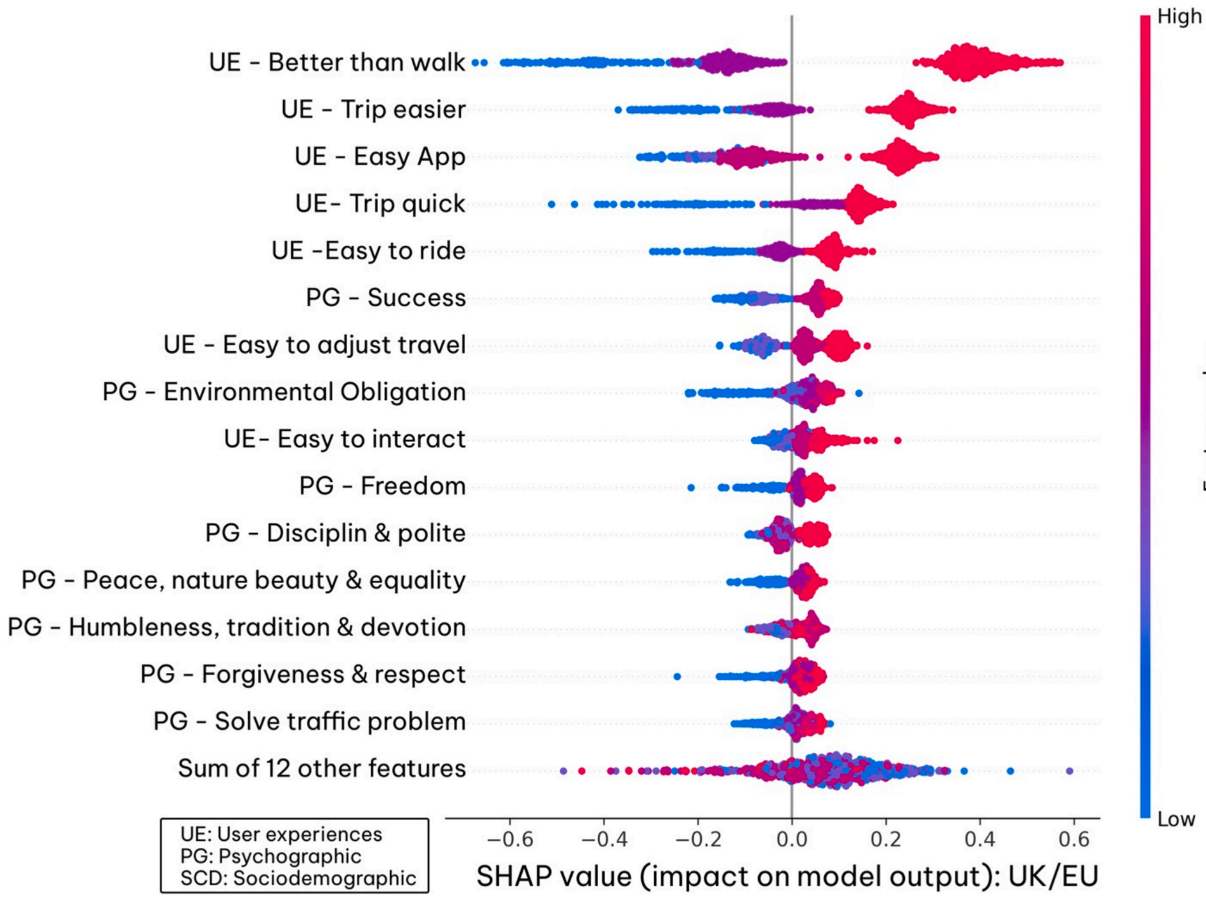

Fig. 5. SHAP Summary Plot – UK/EU.

5. Discussion and conclusion

Understanding shared e-scooter user retention is crucial for promoting and maximising the benefits of this sustainable mode of transportation. By investigating the factors influencing users' future usage, stakeholders can make informed decisions regarding infrastructure development, enhancing the user experience (e.g., App improvements), and mode integration. This study compares the features that may impact existing users' retention in the UK/EU and US, and provides valuable insights.

Most survey respondents in both the UK/EU and US regions were willing to use e-scooters in the future. Only a small percentage of them were "Undecided", "Unlikely", or "Very unlikely" on future usage. However, it is important to note that not all respondents will have future access to e-scooters. This limitation may arise if, for example, an individual is a visitor to a particular location where e-scooters are available, while their hometown does not offer such services.

The CatBoost model demonstrated a good level of accuracy (above 83 %) in both regions in predicting users' future willingness to use e-scooters, and the SHAP analysis provided deeper insights into the effect of various factors on potential retention decisions. Results in the UK/EU and US models show a consistent pattern that shared e-scooter user experience factors were the most important predictors, followed by psychographic and sociodemographic attributes. The low impacts of sociodemographic attributes on shared e-scooter usage align with the findings of Blazanin et al. (2022) since their effects are mediated through psychographic variables.

To improve retention of shared e-scooter services, a combined effort from companies and policymakers is essential, focusing on efficiency, ease of use, environmental impact, and accommodation of diverse needs. Scheme operators may emphasize the time-saving aspect of e-scooters in marketing materials, showing users how e-scooters can shorten their travel time compared to other transport methods. For example, this information could be displayed in the App, making the benefits immediately apparent. Policymakers may also provide designated infrastructure for shared micromobility, like adding special e-scooter/cycle paths, which could make trips quicker and position e-scooters as a superior travel option. In addition, the models show that some of the most important features in the two regions are related to mode change, but the UK/EU focuses on replacing long walks, while the US respondents emphasise adjusting e-scooter to the way (mode) the individual usually travels (e.g., combine with other public transport). This difference will be useful for shaping future priorities on how to incorporate shared e-scooters into the urban transportation system.

Improving the user experience, particularly the ease of use, is also important. Operators need to ensure that the Apps are straightforward to navigate and that the e-scooters themselves are simple to find and use. This is particularly useful for new markets like the UK/EU, where the local population have less knowledge about the service, the App and riding the e-scooters. Gathering and acting on user feedback regularly can be useful for service improvements, thus leading to higher user retention. Stakeholders may work together to set design standards that ensure e-scooter App and vehicles are easy to use and navigate by everyone, including people with disabilities.

Environmental concerns also play a role in user retention, with varying importance in the UK/EU and the US. Stakeholders and policymakers may work alongside environmental groups to highlight the potential eco-friendly benefits of e-scooters, such as lower emissions. Sharing environmental data (e.g., how much CO2 were reduced if replacing a car/taxi trip) can help retain users who are mindful of their ecological footprint. Recharging using clean energy where possible and promoting this aspect may also be helpful for user retention. However,

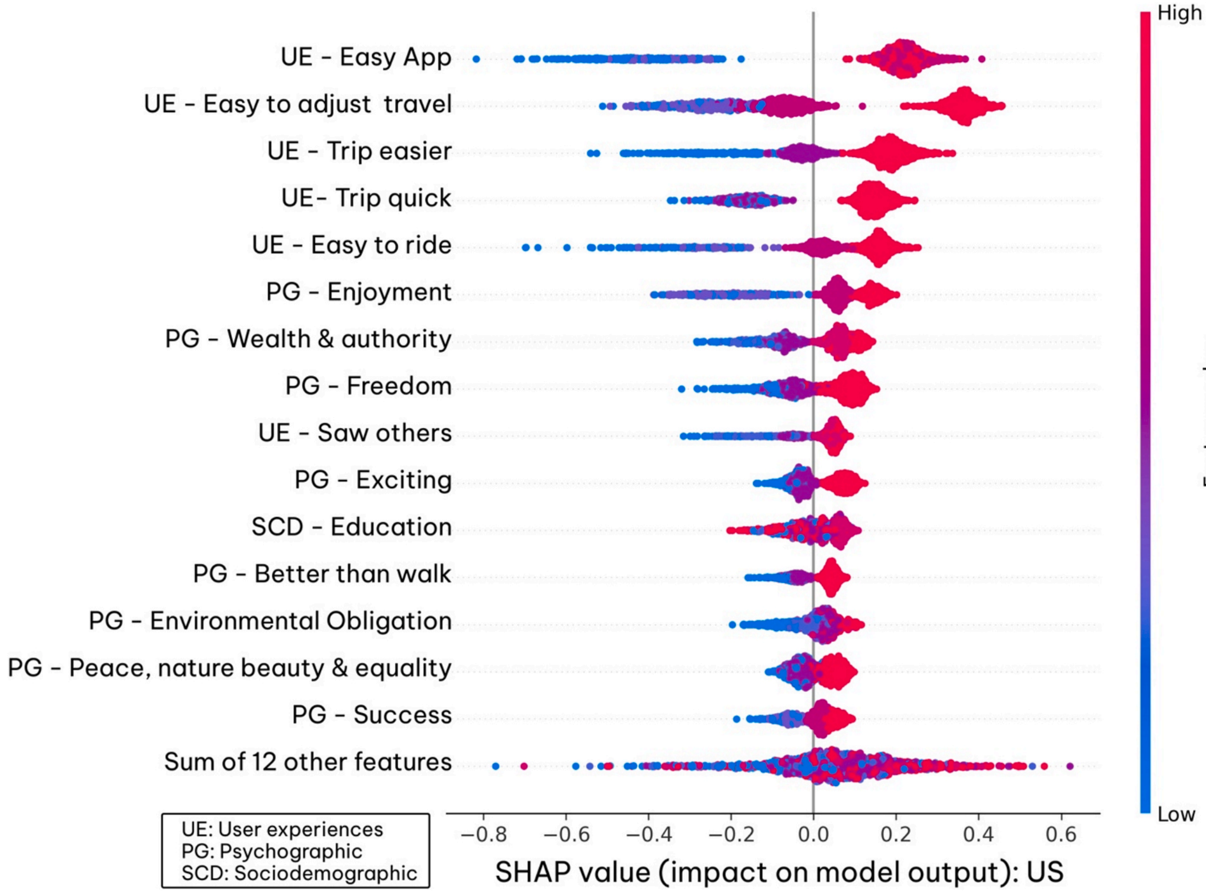

Fig. 6. SHAP Summary Plot – US.

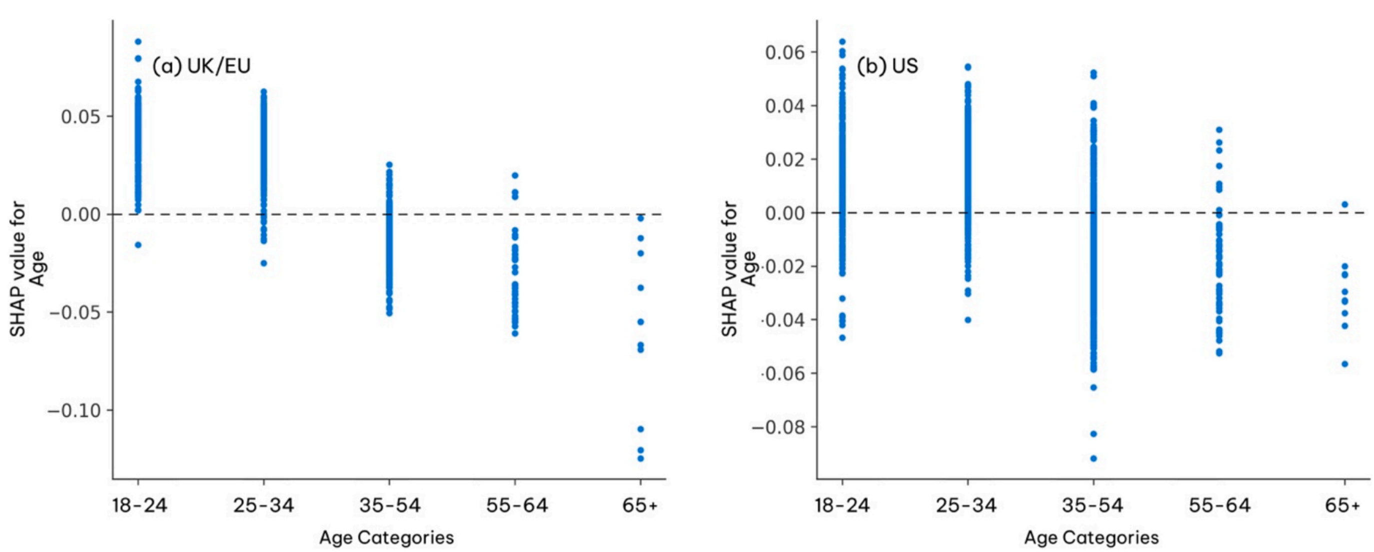

Fig. 7. SHAP dependence plot on age; (a) UK/EU; (b) US.

research on shared e-scooters shows mixed environmental impacts, largely depending on which transportation modes they replace. Their sustainability benefits remain uncertain, varying based on whether users substitute e-scooters for walking (less beneficial) or private cars (more beneficial). This substitution pattern is influenced by both personal and contextual factors, with studies showing varied results across different settings (Félix et al., 2023; Guo et al., 2021). In this study, we observed that UK/EU participants placed greater emphasis on replacing long walking trips when considering continued e-scooter use, whereas US participants did not. The ambiguous environmental benefits of shared e-scooters in different contexts create additional uncertainty when interpreting the influence of environmental awareness factors.

The shared e-scooter service should be more inclusive, for example, older age was found to be a barrier in both regions. Although this is seen in many micromobility services, stakeholders should try to design features that make e-scooters safer and more comfortable for different

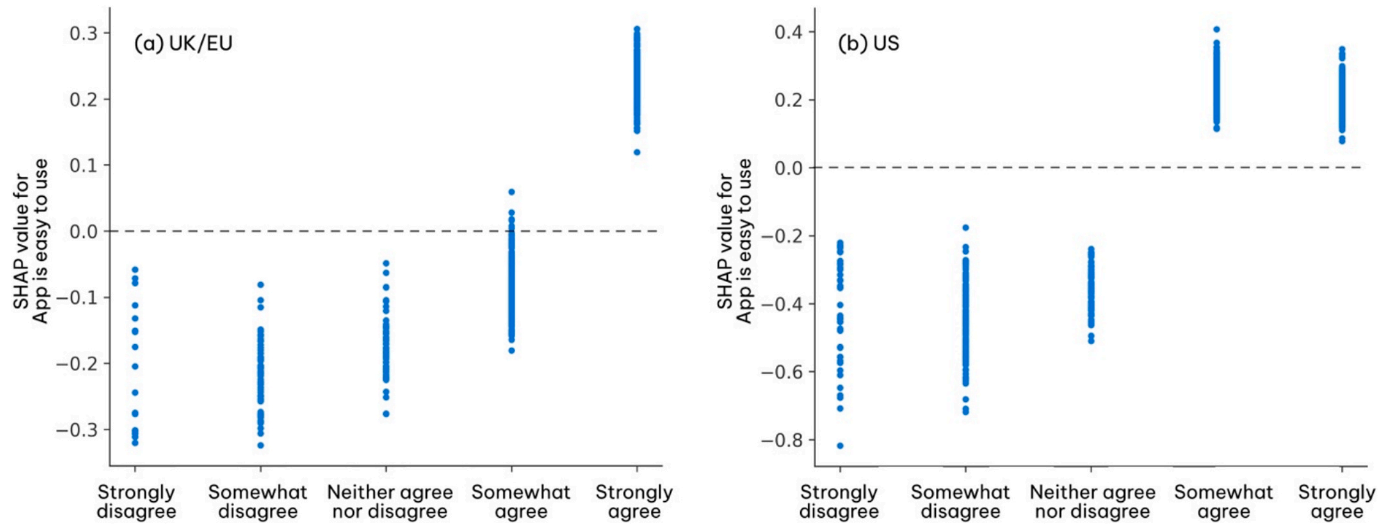

Fig. 8. SHAP dependence plot on the first shared e-scooter trip experience of “App is easy to use”; (a) UK/EU; (b) US.

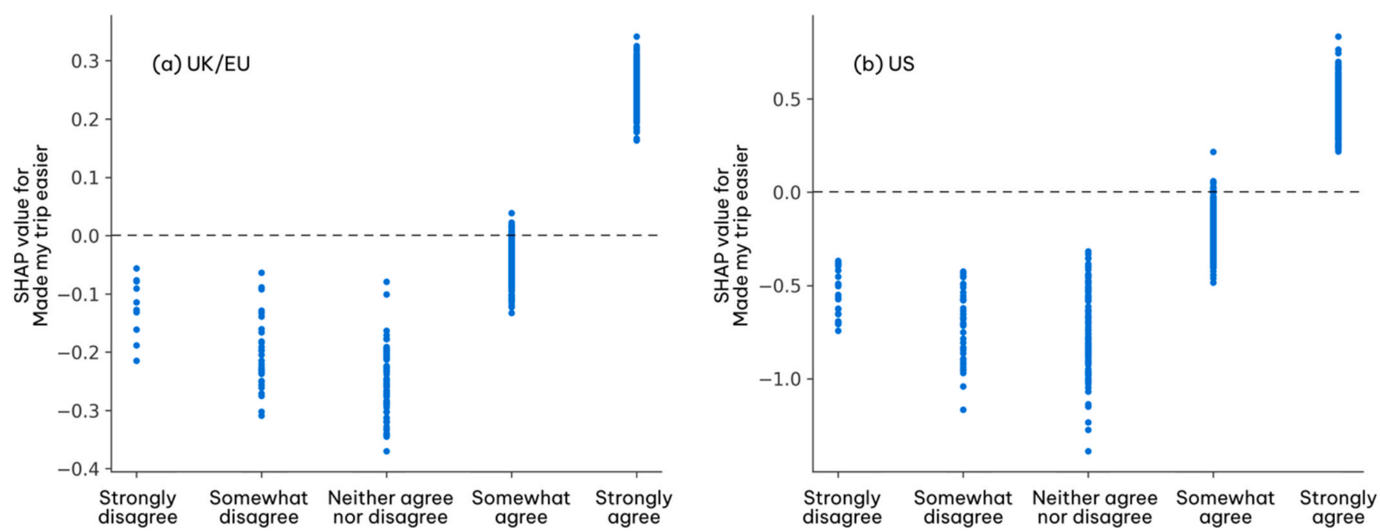

Fig. 9. SHAP dependence plot on the first shared e-scooter trip experience of “Made my trip easier”; (a) UK/EU; (b) US.

groups of individuals, like e-scooters that are stable and easy to mount. Policymakers can ensure public spaces are designed to be e-scooter friendly for users of all ages and abilities, with features like safer pedestrian crossings and e-scooter parking that doesn’t require lifting.

When marketing and promoting the service, the UK/EU and US may need more targeted goals and strategies. For example, it could be beneficial to link the service with the feeling of freedom and flexibility in both regions, but showing the enjoyment and excitement aspects of shared e-scooters will be more effective in the US than in the UK/EU. An emphasis on environmental benefits in the UK/EU may be more effective than in the US for user retention.

It is important to acknowledge a few limitations of this research. There may be potential bias in the data, as it was obtained from people who had used e-scooters at least once. They may not be representative of either the whole cohort of shared e-scooter users or the general population in the study areas. Current users also tend to be predominantly male, young, and more affluent. The results should not be generalised to the broader population or individuals who own a personal e-scooter. The adopted model does not include variables related to meteorological and built environment factors, which may miss important features in other domains. It should be noted that this study relies on participants’ stated intentions to use e-scooters in the future as a key measure. While stated intentions are widely used in transportation and consumer behaviour research, there is a potential gap between intention and action. Prior research has shown that factors such as unforeseen barriers, changing circumstances, and social desirability bias can influence whether stated intentions translate to actual behaviour (Ajzen, 1991; Sheeran and Webb, 2016). This intention-behaviour gap may be especially relevant for emerging mobility services like shared e-scooters in an immature market (e.g., the UK), where user familiarity and access opportunities are still developing. Future studies could enhance this approach by combining stated intentions with follow-up observations of actual usage behaviour.

Moreover, this study could have benefitted from qualitative insights gleaned from responses to an open-ended question allowing participants to share their experiences with e-scooters. Such data could have offered critical insights into user retention factors, highlighting both attractive features and pain points of e-scooter services.

The consolidation of UK and EU participants into a single model, while necessary due to sample size constraints, overlooks significant contextual differences between markets. In England and Wales, e-scooters face strict regulatory limitations, being legal on public roads only through government-approved sharing schemes operating in designated trial areas. These restrictions create artificial usage boundaries that may not align with desired travel patterns, potentially skewing user behaviour and perceptions. For instance, geofenced operational zones may terminate before reaching key destinations, forcing users to complete journeys by other modes.

Meanwhile, UK and EU countries show significant regulatory diversity — the UK prohibits private e-scooters on public roads, while Germany permits them under structured regulations requiring insurance and specific operating conditions. E-scooter use on bike lanes differs by country (e.g. permitted in Germany, prohibited in the UK). Public transport integration also varies dramatically, with some EU cities offering integrated payment systems (like in Finland) and designated parking near transportation hubs, features largely absent in the UK trials. These regulatory, infrastructure, and connectivity differences likely affect adoption, usage frequency, and retention rates in ways that homogeneous market analysis cannot capture.

In addition, the US and UK/EU comparison assumes market maturity differences, with the US representing a more established market while UK/EU markets were relatively nascent during data collection. This temporal distinction is important—as UK/EU markets mature, user perceptions and behaviours likely evolve substantially.

When applying these findings from this study to practice, policymakers and practitioners should consider both the time-sensitivity of market development stages, and regional regulatory frameworks. The results should not be overgeneralised across markets with different characteristics. There is also a need for longitudinal studies to capture evolving user attitudes.

In conclusion, this research provides valuable insights into the future willingness to use shared e-scooters among current users. It compares people's perceptions and factors influencing their decision to retain usage in the UK/EU and US. The knowledge obtained from this study can inform future urban mobility planning and strategies for local shared e-scooter stakeholders and policymakers. Future research may aim to include more diverse data, potentially incorporating similar datasets from different regions or linking individuals' questionnaire surveys with high-resolution trip data. This would provide a more comprehensive understanding of shared e-scooter usage, retention and influencing factors, ultimately contributing to more effective and inclusive urban transportation systems.

CRediT authorship contribution statement

Yuanxuan Yang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Charalampos Saridakis:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Zia Wadud:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Alimurtaza Kothawala:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Aurojeet Jena:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Basar Ozbilen:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Kailai Wang:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Giovanni Circella:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization. **Sebastian Castellanos:** Writing – review & editing, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Susan Grant-Muller:** Writing – review & editing, Project administration, Methodology, Investigation, Data curation, 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.

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Appendix

Table A1
Feature importance ranked from most important to least important in the UK/EU model.

Variable	RI(%)	Rank
Easier to take an e-scooter than have a long or difficult walk	21.17	1
Made my trip easier	12.39	2
My interaction with the e-scooter app was clear and easy to understand	11.44	3
Allowed me to complete my trip more quickly	8.93	4
The e-scooter was easy to ride	4.74	5
Be successful and achieve a high level in my work role	4.49	6
It seemed easy to adjust the way I usually travel by using an e-scooter	4.38	7
Feel a moral obligation to use e-scooters for environmental reasons	3.4	8
The e-scooter was flexible in interacting with other road users	2.41	9
Having the freedom to choose my goals, to be creative, and to be independent	2.26	10
Self-disciplined, honor my elders and to be polite	2.22	11
A world at peace, the beauty of nature and equality	2.19	12
Humbleness, respect for tradition and devotion	2.1	13
Honesty, forgiveness, loyalty, and taking responsibility	1.94	14
Feel personally obliged to tackle traffic related problems by choosing e-scooters in future	1.87	15
Age	1.85	16
Reduce my impact on the environment	1.72	17
I saw a few people trying e-scooters and wanted to try e-scooters too	1.69	18
A friend, colleague, or family member encouraged me to try it	1.5	19
Household income	1.4	20
Having wealth or being in authority in my work role is important to me.	1.27	21

(*continued on next page*)

Table A1 (*continued*)

Variable	RI(%)	Rank
Life is exciting, challenging and varied	1.14	22
Educational attainment	1.03	23
Enjoyment in life, having a few luxuries, and getting the things I want	0.88	24
Car ownership	0.73	25
Gender	0.65	26
Economic activity	0.23	27

Table A2
Feature importance ranked from most important to least important in the US model.

Variable	RI(%)	Rank
My interaction with the e-scooter app was clear and easy to understand	14.3	1
It seemed easy to adjust the way I usually travel by using an e-scooter	13.28	2
Made my trip easier	8.68	3
Allowed me to complete my trip more quickly	8.43	4
The e-scooter was easy to ride	7.22	5
Enjoyment in life, having a few luxuries, and getting the things I want	6.5	6
Having wealth or being in authority in my work role is important to me.	4.6	7
Having the freedom to choose my goals, to be creative, and to be independent	4.4	8
I saw a few people trying e-scooters and wanted to try e-scooters too	3.13	9
Life is exciting, challenging and varied	2.88	10
Educational attainment	2.64	11
Easier to take an e-scooter than have a long or difficult walk	2.51	12
Feel a moral obligation to use e-scooters for environmental reasons	2.26	13
A world at peace, the beauty of nature and equality	2.24	14
Be successful and achieve a high level in my work role	2.19	15
A friend, colleague, or family member encouraged me to try it	1.95	16
Car ownership	1.91	17
Honesty, forgiveness, loyalty, and taking responsibility	1.67	18
Household income	1.49	19
Feel personally obliged to tackle traffic related problems by choosing e-scooters in future	1.42	20
The e-scooter was flexible in interacting with other road users	1.26	21
Reduce my impact on the environment	1.2	22
Age	1.1	23
Gender	0.7	24
Self-disciplined, honor my elders and to be polite	0.78	24
Economic activity	0.68	26
Humbleness, respect for tradition and devotion	0.56	27

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