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User acceptance of smart e-bikes: What are the influential factors? A cross-country comparison of five European countries

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ABSTRACT

Electric bicycles (e-bikes) have been promoted in many countries to replace motorised transport modes and mitigate transport externalities such as traffic congestion and emissions. However, there are also concerns about crash risks and crash severity for e-bike users. Leveraging new technologies could help improve e-bike safety, amongst other safety enhancing measures, but there is little knowledge of the users' acceptance of such technologies. This study aims to explore the user acceptance of e-bikes (pedelec with power assistance up to 25 km/h or speed-pedelec with assistance up to 45 km/h) with active road safety assistance (in short: Smart e-bikes) to improve cycling safety by adopting the extended unified theory of acceptance and use of technology 2 (UTAUT2). A cross-country survey was administered in five European countries-Austria, Belgium, Germany, Greece, and the Netherlands, each differing in population, cycling culture and e-bike market sizes. A sample of 1,589 respondents, including e-bike owners and people interested in buying an e-bike, was analysed using a structural equation model (SEM). Conclusions indicate that performance expectancy, hedonic motivation and perceived safety were the strongest constructs of behavioural intention to use Smart e-bikes in the aggregated sample. All constructs vary significantly across the five countries, which can partly be explained by socio-demographic factors. Geographical factors such as city size, low availability of cycle paths and population density do not explain differences in user acceptance.

1. Introduction

Electric bicycles (e-bikes), an emerging transport mode gaining popularity in recent years (Shimano, 2022), can contribute to reducing emissions and congestion in cities, *peri*-urban as well as rural areas by replacing motor vehicles (Bucher et al., 2019; European Commission, 2019; Fishman and Cherry, 2016; Philips et al., 2022). The recent Covid-19 pandemic and the energy crisis have led to a significant number of people switching to more active transport modes, such as cycling (Buehler and Pucher, 2021, 2023; Nikitas et al., 2021; Shimano, 2022). Shimano (2022) surveyed 12 European countries with over 15,500 participants and found that the high cost of living and higher fuel prices are two leading factors for individuals to buy an e-bike. Additionally, within the last two years, several European research projects have been announced investigating and promoting e-bikes (ETH zürich, 2022; Salzburgresearch, 2022), supporting the assumption of the potential increase in e-bike users. Also, many European countries subsidise purchasing e-bikes or e-cargo bikes. For instance, the Greek government subsidises up to €800, the Austrian government up to €1000, while countries with an

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already high number of cyclists, such as the Netherlands and Belgium, offer a tax reduction (European Cyclists' Federation ECF, 2023). This has resulted in a high number of e-bikes sold in Europe in recent years. In 2021, around five million new e-bikes were sold in Europe (Sutton, 2022), while in 2009, this number was only half a million (Statista, 2020). Note that e-bikes include two categories: Pedelecs (e-bike with pedal assistance up to 25 km/h) and Speed-Pedelec (e-bike with pedal assistance up to 45 km/h) (European Cyclists' Federation ECF, 2017). Thereafter, under the term e-bikes we are referring to both, Pedelecs and Speed-Pedelecs (see Image 1).

With the increasing use of e-bikes, there are also increasing concerns about crash risks and the severity of crashes among e-bike users. In the literature, many studies have been conducted to examine safety-related aspects of e-bike use (Haustein and Møller, 2016; Schepers et al., 2020; Vlakveld et al., 2021), in particular, if there are more safety risks using e-bikes and if injuries are more severe, compared to conventional bikes. A recent literature review also showed that the share of single-bicycle crashes among injured cyclists is about 70 % (Utriainen et al., 2022); and e-bike users are prone to such crashes (Panwinkler and Holz-Rau, 2021). In the Netherlands, 2 out of 3 seriously injured people treated at emergency units are cyclists, and the increasing use of e-bikes is seen as a leading cause of the increase in the number of seriously injured cyclists is growing over time (40 % increase between 2013–2022). In particular, among older cyclists, one-third of this growth is attributed to e-bike use, and among younger cyclists, about 50 % (VeiligheidNL, 2023). Some studies also indicate that crash severity for e-bike users is higher than for conventional cyclists (Panwinkler and Holz-Rau, 2021; Schleinitz and Petzoldt, 2023), although other studies did not find clear differences (Dozza et al., 2016; Schepers et al., 2014). In the literature, speed is found to be one of the leading causes of the high number of e-bike crashes (Haustein and Møller, 2016; Schepers et al., 2014; Stelling et al., 2021), as higher cycling speed influences riding behaviour and the ability to predict movements while in traffic (Huertas-Leyva et al., 2018). Furthermore, many European countries lack sufficient cycling infrastructure, and even countries with well-designed bicycle networks cycling infrastructure are not always designed to cater for the cycling speeds of e-bikes (Statistics Netherlands (CBS), 2021). Moreover, e-bike users' interactions with other non-motorists and safety risks associated with single-bicycle crashes raise concerns. However, this does not imply that the responsibility for reducing these crashes lies with the cyclist. According to traffic rules and road safety hierarchy, the responsibility lies on motor drivers to ensure vulnerable road users safety, such as cyclists and pedestrians (ETSC, 2023; Mullen et al., 2014; Safedrivingforlife, 2023).

In the recent literature, there is an increasing emphasis on preventing e-bike crashes using smart bicycle technologies (Boronat et al., 2021; Oliveira et al., 2021). Such technologies can alleviate cycling safety issues and positively influence cyclists' riding behaviour (Kiefer and Behrendt, 2016). Many studies have been published investigating the development of new smart bicycle features to improve safety and comfort (Boronat et al., 2021; Nikolaeva et al., 2019; Oliveira et al., 2021). Also, an increased feeling of safety is associated with increased comfort (Lu et al., 2018; McNeil et al., 2019; Mekuria et al., 2012). In addition, some cities in the Netherlands have also started exploring the role of technology on bicycles to decrease the high risk of bicycle crashes (Jurre Kuin et al., 2023). Kapousizis et al. (2022) proposed a "Bicycle Smartness Levels" (BSLs) classification for these new technologies focusing on cycling safety, which consists of 6 levels with different safety-enhancing functionalities. These technologies may improve cyclists' safety and comfort in addition to other measures, such as improving the quality of cycling infrastructure, lowering car traffic speeds, etc. (SWOV, 2023). Moreover, some cyclists may feel the need or desire to use smart bicycle technologies. This study aims to investigate the factors influencing users' acceptance of smart bicycle technologies on e-bikes by collecting data and comparing factors across five European countries (Austria, Belgium, Germany, Greece, and the Netherlands). Note that examining the user acceptance of smart bicycle technologies does not imply shifting responsibility for avoiding crashes completely to cyclists, as this also lies with other road users and road authorities. To the author's knowledge, no previous study has investigated user acceptance of Smart e-bikes nor the role of differences in cycling culture and cycling infrastructure across countries. In addition, we established the measurement invariance to draw valid conclusions regarding the comparison among groups.

The cross-country comparison allowed us to examine the acceptance of smart bicycle technologies in countries with fundamental differences in cycling culture, and draw insights for policymakers and industry. To do this, we focused on Level 3 "Active assistance" according to the classification of Kapousizis et al. (2022) considering that this level has the highest technology readiness level and does not employ any communication with other vehicles that needs specific infrastructure. Level 3 consists of the following functionalities: surrounding detection, collision avoidance, speed warnings, post-crash notifications, safer routes and bike-to-infrastructure communication (B2I).

This paper is organised as follows: Section 2 presents the theoretical background, including the conceptual model and hypotheses; Section 3 describes the methodology, survey setup, sample composition, and data; Section 4 reports the research approach and the results; Section 5 discusses the research findings, their implication, future research, and Section 6 closes this work with the conclusions.

2. Theoretical framework

Although extensive research has been carried out on user acceptance in transportation, no single study has investigated the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) on e-bike technology (Venkatesh et al., 2012). The UTAUT and UTAUT2 were extensively used for automated vehicles (AV) use, and even though the proposed Smart e-bike is not automated in nature, one common factor between AV and Smart e-bike is the introduction of new technologies. Thus, the following section describes the UTAUT2 framework and its applications so far, as well as its implementation in Smart e-bikes.

2.1. User acceptance of new technologies in transport

Several studies conducted surveys to investigate public opinion and acceptance of new systems and technologies. Some of those studies focus on user acceptance of AVs (Adnan et al., 2018; Kenesei et al., 2022), automated shuttles (Nordhoff et al., 2020b), autonomous car-sharing services (Curtale et al., 2021), and last-mile delivery using autonomous vehicles (Kapser et al., 2021). These prove that investigating the public acceptance of new applications in transportation-related studies is important to examine users' intentions and help researchers and manufacturers optimally design new systems. The above studies used a wide range of methods spanning from descriptive statistics to advanced theoretical models to examine users' acceptance. The present study utilises one of the most well-known behavioural frameworks for assessing users' acceptance to use new technologies, the UTAUT2 and applies it to bicycle technologies (Venkatesh et al., 2012).

2.2. Adjusting the UTAUT2 model

This study adopted the framework of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012). Previously, the Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed by (Venkatesh et al., 2003), focusing on users' acceptance of new technologies in work environments. UTAUT was built based on other theoretical models, such as the technology acceptance model, theory of planned behaviour, motivational model, and innovation diffusion theory (Venkatesh et al., 2003). However, UTAUT does not consider consumers' technology acceptance (Venkatesh et al., 2012), while UTAUT2 was constructed especially to cover this gap. The UTAUT2 contains four constructs (Performance expectancy, effort expectancy, social influence and facilitating conditions) from the UTAUT model and builds up the rest (hedonic motivation, price value and habit) (Venkatesh et al., 2012). While, as we mentioned, the original UTAUT2 model specifies seven constructs (Venkatesh et al., 2012), we adjusted the model to fit this study's aim better. Since the initial UTAUT model was developed focusing on users' acceptance and use of technology in work environments (Venkatesh et al., 2003; Venkatesh et al., 2012), adjustments to the models are common in transport research. For instance, Kapser et al. (2021) studied the acceptance of autonomous delivery vehicles and adjusted the model by excluding the constructs habit and price value since autonomous delivery vehicles were not yet available. However, they added perceived risk and price sensitivity as constructs. Curtale et al. (2021) also excluded facilitating conditions, price value and habit since these constructs tend to predict the actual use rather than intention due to the lack of available automated electric car-sharing services. Finally, a study related to bicycle-sharing systems conducted by Jahanshahi et al. (2020) excluded habit and hedonic motivation and included perceived safety as a construct.

2.3. Conceptual model of Smart e-bikes

To develop a theoretical model that fits best in this study, we have adapted the UTAUT2 model. More specifically, following other studies (Jahanshahi et al., 2020; Kapser et al., 2021) we included perceived safety as a construct as well as social status since it has been proved that it plays a key role in people's psychological behaviour (Jahanshahi et al., 2020; Simsekoglu and Klöckner, 2019a). However, we excluded facilitating conditions, price value, and habit of the UTAUT2 model since the Smart e-bike is hypothetical and not commercially available yet. Fig. 1 displays the conceptual model for this study.

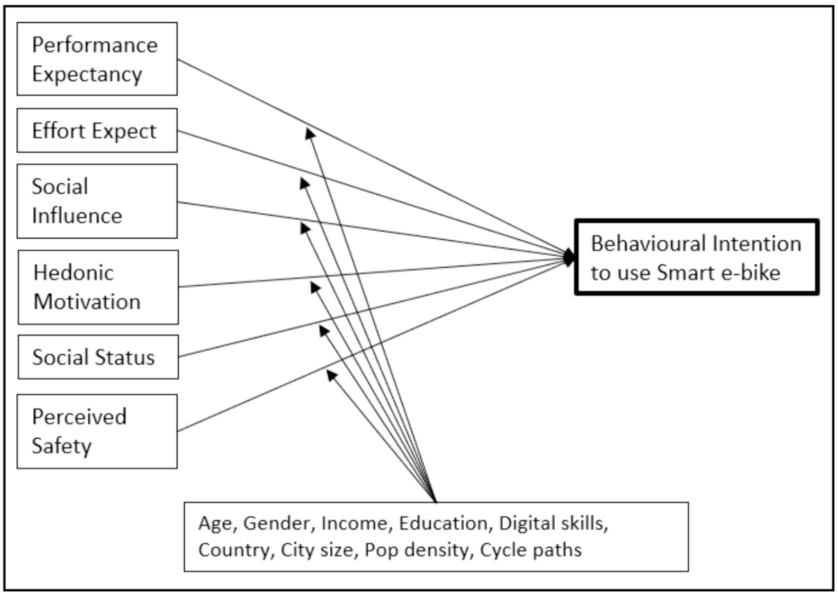

Fig. 1. Conceptual model for the user acceptance of Smart e-bikes.

2.3.1. Research hypotheses

It is hypothesised that behavioural intention to use the Smart e-bike is related to performance and effort expectancy, social influences, hedonic motivation, social status and perceived safety. The elements in the conceptual model are as follows:

Performance expectancy relates to the individual beliefs concerning a system and the help an individual gains when using it (Venkatesh et al., 2003). Having a closer look at the transportation domain, there are many studies which have investigated users' acceptance of AVs (Curtale et al., 2021; Nordhoff et al., 2020a). These studies have found that this construct has a positively strong impact on behavioural intention. In addition, performance expectancy has a positive and strong relationship in research studies investigating the intention to use e-bikes and shared e-bikes (Simsekoglu and Klöckner, 2019a; Yasir et al., 2022). In the context of this study regarding the Smart e-bike, we assume that the performance expectancy construct will also be a strong predictor since the Smart e-bike could improve user comfort and mobility. Also, since we perform a cross-country analysis, we believe that performance expectancy will be a strong predictor for all the countries.

Effort expectancy refers to the ease of use of a specific system (Venkatesh et al., 2003) and is also associated with the degree of consumer's ease of use (Venkatesh et al., 2012). Effort expectancy shows a positive influence in studies related to AV acceptance (Buckley et al., 2018; Golbabaei et al., 2020), while other studies have proved that the influence of effort expectancy is low but positive as well (Nordhoff et al., 2020a). Also, previous studies on bicycles found that effort expectancy has a frugal influence on behavioural intention (Jahanshahi et al., 2020; Wolf and Seebauer, 2014). Therefore, in the context of the Smart e-bike we believe that effort expectancy will have positive influence on behavioural intention.

Social influence is defined as an individual's perception of what others believe they should follow for a specific technology and to what extent others' opinion influences an individual to accept and use technology (Venkatesh et al., 2003). In the literature, social influence is a positive predictor of behavioural intention in many studies investigating the use of AVs (Kapser et al., 2021; Nordhoff et al., 2020a). However, Jahanshahi et al. (2020) could not support this hypothesis in a bicycle-sharing system study. With respect to the previous studies, it is hypothesised that social influence will positively influence behavioural intention to use Smart e-bikes.

Hedonic motivation proves the enjoyment an individual can sense using a technology (Venkatesh et al., 2012). This construct positively discloses users' intention to accept technology in transportation, especially in AVs (Kapser et al., 2021; Nordhoff et al., 2020a). Hence, it could conceivably be hypothesised that hedonic motivation will positively impact behavioural intention to use a Smart e-bike.

In addition to the main constructs of the UTAUT2, we extended the model by using two more constructs, namely **social status,** and **perceived safety**. Social status refers to practices that individuals do because they believe they belong to a specific social group and/or their beliefs about their status (Jahanshahi et al., 2020; Simsekoglu and Klöckner, 2019a). Perceived safety has been used by Jahanshahi et al. (2020); Kapser et al. (2021) as a construct to predict the intention to use shared bicycles and autonomous delivery vehicles. In this study, perceived safety predicts how the intention to use Smart e-bikes is influenced by an individual's belief that the Smart e-bike will improve their safety. The hypotheses derived from the behavioural framework are as follows:

H1: Performance expectancy positively influences behavioural intention to use a Smart e-bike.
H2: Effort expectancy positively influences behavioural intention to use a Smart e-bike.
H3: Social influence positively influences behavioural intention to use a Smart e-bike.
H4: Hedonic motivation positively influences behavioural intention to use a Smart e-bike.
H5: Social status positively influences behavioural intention to use a Smart e-bike.
H6: Perceived safety positively influences behavioural intention to use a Smart e-bike.

Furthermore, we also developed sixteen sub-hypotheses, presented in Table 1, together with the paths and the proposed effect of each variable. We hypothese that socio-demographic characteristics, especially high-income and highly educated people as well as the elderly (considering the risk averseness), would positively impact the behavioural intention to use the Smart e-bike (H7a-H7d). People who are technology-friendly and aware of the benefits of new technologies, such as people with high digital skills and those who know about advanced driving assistance systems (ADAS) will also positively influence behavioural intention (H8a and H8b) (Wolff and Madlener, 2019). Traffic-related and safety-related characteristics, such as lack of cycling infrastructure, low perceived safety, and high traffic density, would also positively impact behavioural intention (H9a-H9d) due to the safety advantages the Smart e-bike can bring. Similarly, geographical characteristics such as population density, city size and availability of cycle paths would positively impact behavioural intention (H10a-H10d), since potential users living in such areas can benefit from the Smart e-bike characteristics such as B2I. We also hypothesise that the behavioural intention to use a Smart e-bike varies among countries, in addition to individual characteristics, due to the differences in cycling culture and levels of infrastructure; hence, we expect heterogeneity between countries towards behavioural intention (H11).

3. Methodology

3.1. Survey setup and recruitment

For this study, a tailor-made web-based survey using the Lighthouse Studio platform (Sawtooth Software, 2022) was developed. The survey was administered by fully complying with the General Data Protection Regulation (GDPR). In addition, the security issues for the survey were addressed. Lastly, Ethical approval for this survey was obtained by the Human Research Ethics Committee (HREC) at the University of Twente.

The survey was administered in four phases: three pilot test versions and the final distribution. The first phase falls into the survey distribution among the researcher group members to ensure the optimal structure and reliability of the survey. Afterwards, the survey

Image 1. Graphical representation of a Smart e-bike.

Table 1
Sub-hypotheses.

Hypothesis	Path	Proposed effect
H7a	Gender (male) → BI	+
H7b	Age → BI	+
H7c	Age (older than 60) → BI	+
H7d	Education (high) → BI	+
H7e	Income (high) → BI	+
H8a	Digital skills (high) → BI	+
H8b	ADAS (yes) → BI	+
H9a	Lack of infrastructure (high) → BI	+
H9b	Perceived safety (high) → BI	+
H9c	Traffic density (high) → BI	+
H9d	Crash (yes) → BI	+
H10a	Population density (high) → BI	−
H10b	City size (<50 k) → BI	+
H10c	City size (>500 k) → BI	+
H10d	Cycle paths (few) → BI	−
H11	Countries are heterogenous → BI	≠
BI: Behavioural intention		

was translated into five languages (Dutch, English, German, Greek, and French). In the second phase, we sent the translated version of the survey to fourteen experts across the selected countries; nine of them participated and sent their suggestions. Then, in the third phase, we distributed the survey to twenty random respondents per language/country to ensure the layman's translation was clear. Lastly, we officially distributed the survey in a web-based online format among the target countries. The responses from the research group members and the experts were discarded, while the responses from random people were included in the analysis.

The online survey was conducted in Austria, Belgium, Germany, Greece and the Netherlands between November 2022 and January 2023, targeting both existing and potential e-bike users. The choice of these target groups derives from the perspective of collecting from people interested in cycling, especially on e-bikes. Note that the survey distinguished between Pedelecs (up to 25 km/h) and Speed-Pedelec (up to 45 km/h) (European Cyclists' Federation ECF, 2017). The survey was distributed through European Cyclists' Federation (ECF) members, cycling unions, and social media. In the Netherlands, we used a mixed-method approach by distributing the survey online and on-site. We visited a bicycle experience centre in Ede, the Netherlands for the on-site distribution. Ede is located in the middle of the Netherlands and welcomes visitors from all over the country to test different types of bicycles. The reason for this choice of the mixed-method was twofold, 1) to get as many participants as possible who are unfamiliar with the technologies (e.g. do not use smartphones or computers) and could not participate in the online survey, namely elderly and low-income people, and 2) to recruit people who are buying an e-bike. In addition, to ensure representative samples, a second group of respondents were recruited through a panel market research, panelclix.[1]

Furthermore, the countries were not selected randomly; on the contrary, we chose them due to the different quality of cycling infrastructure to understand people's perceived safety and cycling culture. These countries vary in size, cycling rate and cycling safety.

[1] https://www.panelclix.co.uk/.

While the Netherlands has a high-quality cycling infrastructure, a dense network, and high bicycle rate (Schepers et al., 2017), Belgium and Germany have medium cycling infrastructure and bicycle rates, while Austria has medium to low ones. On the other hand, Greece has a scarce and low quality infrastructure network and low cycling rate (European Commission, 2020).

3.2. Survey design

The survey consisted of three parts. Firstly, the participants were introduced to the survey concept, and screening questions such as mobility habits and familiarity with new technologies were asked. The second part refers to UTAUT2-related questions about psychological constructs affecting the use of a Smart e-bike. All the questions were designed based on a five-point Likert scale (Table 2) (Venkatesh et al., 2003; Venkatesh et al., 2012). To avoid bias in our data due to participants' unfamiliarity with the smart technologies on bicycles, participants received a description of the Smart e-bike in plain layperson language and a representation of a graphical scenario before entering the UTAUT2-related questions as follows (Kyriakidis et al., 2015):

In the following questions, you will be asked to give your opinion about a smart electric bicycle, the Smart e-bike.

- *The Smart e-bike is equipped with various systems to improve your comfort and safety while cycling. You always maintain the steering control of the bicycle.*
- *The Smart e-bike will warn you and/or automatically reduce its speed in order to avoid a collision with other bikes, vehicles, or pedestrians.*
- *The Smart e-bike will request green at traffic lights. You will need to stop fewer times, and your travel time can be shorter.*
- *The Smart e-bike will automatically send an SMS/call to emergency units in case you have involved in a severe crash.*
- *The Smart e-bike will recommend safer routes for you.*

Below you can see a representation of how a Smart e-bike would look like:

Thus, participants were able to understand better the features of the Smart e-bike and more details about their use. The third and last part refers to the socio-demographic characteristics of the participants.

While other alternatives exist assisting cyclists to get green traffic lights (green wave), such as the Green Waves for bicycles in Copenhagen (Centreforpublicimpact, 2016) and computer vision cameras identifying bicycles approaching (vivacitylabs.com, 2024), we focused on wireless technology since it can achieve communication between traffic lights and bicycles in a longer range and ensure the priority to the latter (Ben Fredj et al., 2023).

3.3. Sample description

In total, 1,625 people who own an e-bike or are interested in buying one completed the survey in the target countries. Responses with less than 5 min of completing time and no variation in the Likert scale questions were excluded from further analysis (a total of 36 respondents). Thus, after the data cleaning, 1589 responses remained. Table 3 shows the sample characteristics. In detail, 48 % (762) of the total sample own an e-bike, while the rest, 52 % (827), is willing to buy one. 45 % (699) of the respondents live in a town smaller than 50,000 citizens, while 43 % (638) and 12 % (187) respondents live in a city size between 50,000–500,000 and higher than 500,000, respectively. The Netherlands' sample is representative according to the Mobility Panel Data (KiM, 2021) for e-bike users. There is no available database for cyclists to compare our samples for the rest of the countries.

3.4. Geographical data

In the survey, we asked participants to provide their home postcodes. We obtained 1,524 correct postcodes out of 1,589. More specifically, we had the full postcodes for 79 respondents from Austria, 269 from Belgium, 90 from Germany, 212 from Greece, and 874 from the Netherlands. To identify the geographical home locations of the respondents, we used the Postal codes dataset provided by (Eurostat, 2022) and merged it with the available 1524 postcodes. Table 3 shows the sample composition per country.

In addition, we used the home postcodes data to identify the city size, population density and the available cycling infrastructure for the respondents' home area. We used OpenStreetMap (2023) data to get the cycle infrastructure, the Nomenclature of Territorial Units for Statistics 3 (NUTS3), and Administrative Units from Eurostat to get the population density and city size. Using ArcGIS (ESRI, 2022), a buffer zone of 10 km was developed for each postcode centroid to identify the entire cycling infrastructure per postcode in each country.

3.5. Analysis approach

A variety of methods and steps were used to assess the Structural Equation Model (SEM). The analysis included exploratory factor analysis (EFA) followed by confirmatory factor analysis (CFA) and the SEM estimation. The EFA was conducted in Python (Van Rossum and Drake Jr, 1995) using the Principle Axis Factoring and Varimax rotation with the average sum of Cronbach's alpha = 0.926 and KMO (Kaiser-Meyer-Olkin) = 0.946, confirming its suitability for CFA and SEM estimation. The CFA and the SEM model were estimated using the SPSS-AMOS software (Arbuckle, 2022) employing the robust Maximum Likelihood estimator.

Table 2
Constructs, statements, and sources.

	Constructs	*Main sources*
Performance Expectancy (PE)		
PE1	I expect that a Smart e-bike would be useful for me	(Simsekoglu and Klöckner, 2019b; Venkatesh et al., 2012)
PE2	Using a Smart Bike would help me reach my destination, within a city, more comfortably	
PE3	I expect that a Smart e-bike would be useful for achieving my daily mobility needs	
Effort Expectancy (EE)		
EE1	It would be too much effort for me to pay attention to the systems of a Smart e-bike	(Nordhoff et al., 2020a; Simsekoglu and Klöckner, 2019b; Venkatesh et al., 2012)
EE2	It would be too time consuming for me to learn how to use a Smart e-bike	
EE3	I will ride with more stress using a Smart e-bike	
Social Influence (SI)		
SI1	I believe that people who are important to me think that I should use a Smart e-bike	(Curtale et al., 2021; Jahanshahi et al., 2020; Venkatesh et al., 2012)
SI2	I expect that people who are important to me would encourage me to use a Smart e-bike	
SI3	I expect that people whose opinions I value would prefer that I use a Smart e-bike	
Hedonic Motivation (HM)		
HM1	Riding a Smart e-bike would be enjoyable for me	(Kapser et al., 2021; Nordhoff et al., 2020a; Venkatesh et al., 2012)
HM2	Riding a Smart e-bike would be much more enjoyable than a conventional bicycle for me	
HM3	Riding a Smart e-bike would be cool	
Social Status (SS)		
SS1	I would feel part of a group/community using a Smart e-bike	(Jahanshahi et al., 2020; Simsekoglu and Klöckner, 2019a)
SS2	Riding a Smart e-bike will be in line with my social class	
SS3	I would be proud if people saw me owning a Smart e-bike	
Perceived Safety (PS)		
PS1	I believe that a Smart e-bike will increase my safety (when riding) compared to a conventional bicycle	(Jahanshahi et al., 2020) *and own investigation*
PS2	I think that riding a Smart e-bike can reduce the risk of me getting involved in a crash/ collision compared to a conventional bicycle	
PS2	I think that there will be fewer severe crashes for the Smart e-bike users	
Behavioural Intention (BI)		
BI1	I would like to buy a Smart e-bike when it will be on the market in the future	(Nordhoff et al., 2020a; Pan et al., 2022; Venkatesh et al., 2012)
BI2	I would like to choose a Smart e-bike even though it is more expensive	

EE1 to EE3: Likert scale scoring has been reversed for the analysis.

3.6. Multigroup analysis and measurement invariance

This study utilises multigroup analysis to examine differences between the acceptance of Pedelec and Speed-Pedelec and between respondents from five countries. Measurement invariance (MI) is the main method used to determine whether a construct is equivalently perceived across groups and whether the comparisons made are meaningful (Putnick and Bornstein, 2016). However, multigroup analysis in the transportation domain often lacks MI assessments. Based on the literature (Putnick and Bornstein, 2016; Vandenberg and Lance, 2000), we compared three models: configural (M1), metric (M2), and scalar invariance (M3) to test MI. Comparisons of the RMSEA and CFI fit indices are commonly used. The fit values are < 0.015 and ≤ 0.01 for the ΔRMSEA and ΔCFI, respectively (Chen, 2007; Cheung and Rensvold, 2002). However, the fit value for ΔCFI varies among researchers and some use more liberal fit ($\Delta\text{CFI} \leq 0.02$) due to different model parameters such as sample size, number of groups, and number of factors (Cheung and Rensvold, 1999; Putnick and Bornstein, 2016).

4. Research approach and results

4.1. Structural equation model

The CFA contains seven constructs and 20 variables (Table 4). Hair et al., (2014,p. 618) put a threshold for the standardised loading above 0.5 and ideally above 0.7. In this study, standardised factor loading varies mainly from 0.703 to 0.947, except for one variable, EE1, which was 0.640, with the accepted threshold at 0.5 (Hair et al., 2014). Table 4 presents the factor loadings and the descriptive statistics, i.e., each variable's mean, standard deviation, skewness, and kurtosis.

The goodness of fit of the model was evaluated using the following measurements: chi-square test of model fit (CMIN/DF) = 3.878, Comparative Fit Index (CFI) = 0.982, Tucker-Lewis index (TLI) = 0.977, Root Mean Square of Approximation (RMSEA) = 0.043, Standardised Root Mean Square Residual (SRMR) = 0.0253 and Parsimony Fit Index (PNFI) = 0.761 (Hair et al., 2014; Schumacker and Lomax, 2010). Those indexes are also commonly used in many transportation studies (Curtale et al., 2021; Kapser et al., 2021; Nordhoff et al., 2020a; Sarker et al., 2019). As was expected, due to the large sample, the test of exact fit indicated not entirely adequate results, with $\chi^2 = 573.926$. Table 5 displays all the assessments with their cut-offs. In addition to the above tests, we assessed the construct validity of our model. Construct validity refers to what extent the variables which comprise a construct are converged and to the degree these variables are not interrelating with other constructs. Various tests are available for construct validity, such as Nomological (Cronbach and Meehl, 1955) and Multitrait-Multimethod Matrix (Campbell and Fiske, 1959). We assessed the model for convergent and discriminant validity, which are subtypes of construct validity and the most commonly used (Kapser et al., 2021; Nordhoff et al., 2020a). Cronbach's alpha and composite reliability (CR) were above the acceptance threshold of 0.7 for all constructs

Table 3
Sample composition.

Variable	Austria	Belgium	Germany	Greece	Netherlands	Total
Number of respondents	80 (5)	271 (17)	124 (8)	231 (15)	883 (55)	1589 (100)
Gender						
Male	58 (73)	169 (62)	85 (69)	171 (74)	425 (48)	908 (57)
Female	18 (23)	99 (37)	37 (30)	59 (26)	444 (50)	657 (42)
Non-binary	3 (4)	1 (0)	0	0	4	8 (0)
Other/prefer not to answer	1 (1)	2 (1)	2 (2)	1 (0)	10 (1)	16 (1)
Age						
18–29	3 (4)	15 (6)	12 (10)	27 (12)	44 (5)	101 (6)
30–39	17 (21)	37 (14)	16 (13)	61 (26)	113 (13)	244 (15)
40–49	12 (15)	51 (19)	19 (15)	70 (30)	113 (13)	265 (17)
50–59	24 (30)	54 (20)	39 (31)	51 (22)	194 (22)	362 (23)
60–69	18 (23)	78 (29)	31 (25)	22 (10)	226 (10)	375 (24)
>70	6 (8)	36 (13)	7 (6)	0	193 (22)	242 (15)
Education						
Low (high school or lower)	28 (35)	72 (27)	35 (28)	60 (26)	459 (52)	654 (41)
High (university degree or higher)	52 (65)	199 (73)	89 (72)	171 (74)	424 (48)	935 (59)
Net monthly income (€/month)						
Low (until 2000)	23 (29)	58 (21)	34 (27)	180 (78)	285 (32)	580 (37)
High (more than 2000)	42 (53)	175 (65)	69 (56)	32 (14)	478 (54)	796 (50)
Prefer not to answer	15 (19)	38 (14)	21 (17)	19 (8)	120 (14)	213 (13)
E-bike ownership						
Pedelec	35 (44)	119 (44)	62 (50)	28 (12)	429 (49)	673 (42)
SPX	0	48 (18)	3 (2)	6 (3)	32 (4)	89 (6)
Willing to buy an e-bike within five years						
Pedelec	42 (53)	82 (30)	55 (44)	154 (67)	388 (44)	721 (45)
SPX	3 (4)	22 (8)	4 (3)	43 (19)	34 (4)	106 (7)
City size						
Less than 50 k	22 (28)	183 (68)	28 (23)	93 (40)	373 (42)	699 (46)
50–500 k	17 (21)	62 (23)	25 (20)	95 (41)	439 (50)	638 (42)
More than 500 k	40 (50)	24 (9)	37 (30)	24 (10)	62 (7)	187 (13)
Population density*						
Low (0–462)	39 (49)	113 (42)	55 (17)	122 (53)	399 (45)	750 (47)
High (463–20.965)	40 (50)	156 (58)	69 (56)	90 (39)	484 (55)	839 (53)

* Population density refers to people per km^2 by NUTS3; number in brackets indicate the percentage (%)

Table 4
Results of factors loadings and descriptive statistics.

Construct	Item	Factor loading$^¥$	M	SD	Skew	Kurt
Performance Expectancy	PE1	0.901***	3.36	1.10	−0.566	−0.333
	PE2	0.877***	3.35	1.10	−0.597	−0.315
	PE3	0.832***	3.14	1.14	−0.352	−0.665
Effort Expectancy	EE1	0.640***	2.99	0.98	0.065	−0.503
	EE2	0.703***	3.53	0.98	−0.371	−0.314
	EE3	0.715***	3.39	1.04	−0.332	−0.493
Social Influence	SI1	0.899***	2.83	1.08	0.070	−0.647
	SI2	0.943***	2.83	1.08	0.101	−0.718
	SI3	0.908***	2.82	1.07	0.361	−0.841
Hedonic Motivation	HM1	0.881***	3.43	1.03	−0.766	0.213
	HM2	0.826***	3.01	1.17	−0.152	−0.811
	HM3	0.851***	3.05	1.16	−0.299	−0.713
Social Status	SS1	0.748***	2.28	1.08	0.441	−0.716
	SS2	0.725***	2.61	1.12	0.014	−0.791
	SS3	0.856***	2.36	1.17	0.361	−0.841
Perceived Safety	PS1	0.903***	3.45	1.00	−0.678	0.095
	PS2	0.813***	3.29	1.01	−0.630	−0.195
	PS3	0.750***	3.21	1.00	−0.483	−0.247
Behavioural Intention	BI1	0.947***	3.00	1.09	−0.359	−0.676
	BI2	0.848***	2.80	1.09	−0.118	−0.914

***: p-value < 0.001; M = mean; SD = standard deviation; Skew = skewness; Kurt = kurtosis; $^¥$ standardized

(Hair et al., 2014). The Average Variance Extracted (AVE) was above the cut-off criterion of 0.50 (Fornell and Larcker, 1981; Hair et al., 2014), 0.477 for effort expectancy, illustrating the convergent validity. Despite the AVE for effort expectancy being at the limit, we retained it since the AVE is often too strict, and reliability can be established through the CR only (Malhotra and Dash, 2011). Hence the assessment supports internal consistency. In addition, the Fornell-Larker criterion was assessed, which indicates discriminant

Table 5
Model fit indices.

Model fit assessment	χ^{2*}	CMIN/DF	CFI	TLI	RMSEA#	SRMR	PNFI
Cut-off	–	< 5.0	≥ 0.95	≥ 0.95	≤ 0.07	< 0.05	> 0.5
Results	573.926	3.878	0.982	0.977	0.043	0.0253	0.761

* (df = 148, p-value < 0.001); # with a 90 % confidence interval of [0.039; 0.046]

validity; the square root of the AVE of each construct surpass all the correlation among the constructs (Fornell and Larcker, 1981). All those assessments are reported in Table 6. However, Franke and Sarstedt (2019) recently concluded that the Fornell-Larker criterion could not properly identify the discriminant validity. Hence, as an addition, we employed the Heterotrait-Monotrait ratio correlation (HTMT) (Henseler et al., 2014). The values of the HTMT were below the threshold of 0.85 and can be found in Appendix A.

4.2. Measurement invariance

Table 7 presents the results of the MI-Pedelec and Speed-Pedelec and-MI Country, indicating that the behavioural intention to use Smart e-bikes across the five countries and among the two groups of e-bikes attained the scalar invariance. This means invariance among those groups (i.e. countries and e-bikes) reached, hence the comparison made is meaningful and the multigroup analysis can be conducted. Note that the ΔCFI in MI-Country M3 slightly exceeds the cut-off; however, we proceeded with the analysis since the ΔRMSEA is well below its cut-off and since it is not easy to achieve MI with many groups (Putnick and Bornstein, 2016). In addition, scalar invariance is rarely tested and established (Putnick and Bornstein, 2016; Vandenberg and Lance, 2000).

4.3. SEM results

A significant positive relationship was found between performance expectancy and behavioural intention, effort expectancy and behavioural intention, social influence and behavioural intention, hedonic motivation and behavioural intention, and perceived safety and behavioural intention. In contrast, there is no significant relationship between social status and behavioural intention. The hypotheses and their structural results are presented in Table 8. The variability of behavioural intention to use a Smart e-bike is explained by 80 % of the proposed model.

4.4. Socio-demographic, geographic and safety-related effects on constructs

Socio-demographic characteristics affect all the UTAUT2 constructs, and heterogeneity exists among them (Table 9). All the variables for the following analysis are dummy-coded. Performance expectancy significantly increases for all the variables that were tested. Effort expectancy increases for males, people older than 60, high income, and areas lacking cycling infrastructure. Also, it increases significantly for people with high digital skills using a smartphone and in high-density areas. Social influence decreases in high-traffic density areas and increases with the increase in city size and people unfamiliar with ADAS. For the rest of the variables, it significantly increases. Hedonic motivation shows a significant effect across all the variables, while there is no educational impact on hedonic motivation. Social status increases with age, income, perceived safety and lack of cycling infrastructure, and there is no effect for the other variables. Perceived safety significantly increases with all the variables, while there is no effect with the technology and the cycle paths.

4.5. Multigroup analysis

4.5.1. Behavioural intention to use a Pedelec and Speed-Pedelec

Psychological constructs, socio-demographic characteristics, geographical and safety-related effects on behavioural intention are presented in Table 10. All the UTAUT2 constructs positively affect behavioural intention to use a Smart Pedelec except the social status. Performance expectancy, hedonic motivation and perceived safety have the most substantial impacts, followed by social

Table 6
Convergent validity, construct reliability, and Fornell–Larcker criterion.

	α	CR	AVE	PE	EE	SI	ST	HM	PS	BI
PE	0.904	0.903	0.757	**0.870**						
EE	0.728	0.728	0.477	0.458	**0.687**					
SI	0.940	0.941	0.841	0.697	0.281	**0.917**				
ST	0.819	0.821	0.605	0.650	0.275	0.675	**0.778**			
HM	0.890	0.889	0.728	0.823	0.536	0.651	0.725	**0.853**		
PS	0.885	0.865	0.680	0.737	0.515	0.618	0.594	0.772	**0.825**	
BI	0.891	0.894	0.808	0.844	0.492	0.685	0.671	0.842	0.758	**0.899**

α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.Bold elements on the diagonal of the construct correlation matrix represent the square roots of the AVE.

Table 7
Comparison of the nested models.

Model	χ^2	df	χ^2_{diff}	Δdf	RMSEA [90 % CI]	ΔRMSEA	CFI	ΔCFI
MI-Pedelec and Speed-Pedelec								
M1	742.905	296	–	–	0.031 [0.028–0.034]	–	0.981	–
M2	753.47	309	10.565	13	0.030 [0.027–0.034]	0.001	0.9982	0.001
M3	784.987	322	31.517***	13	0.030 [0.027–0.034]	0.000	0.981	0.001
MI-Country								
M1	1278.064	740	–	–	0.021 [0.019–0.023]	–	0.977	–
M2	1346.489	792	68.425*	52	0.021 [0.019–0.023]	0.000	0.976	0.001
M3	1715.481	844	368.992***	52	0.026 [0.024–0.027]	0.005	0.963	0.013

MI: Measurement invariance, MI-Country: Measurement invariance for the countries, MI-Pedelec and Speed-Pedelec: Measurement invariance for e-bike groups, M1: configural invariance, M2: metric invariance, M3: scalar invariance, ***: p-value < 0.001, *: p-value < 0.1

Table 8
Results of structural relationships.

Hypothesis	β_{std}	p-value	Results
H1	0.394	<0.001	supported
H2	0.037	0.004	supported
H3	0.080	<0.001	supported
H4	0.356	<0.001	supported
H5	0.027	0.132	rejected
H6	0.112	<0.001	supported

βstd: Standardised regression coefficient

Table 9
Socio-demographic effects on constructs.

Variables	PE	EE	SI	HM	SS	PS
	βstd	βstd	βstd	βstd	βstd	βstd
Gender (male)	0.386***	0.036**	0.080***	0.376***	0.031	0.106***
Age (>60)	0.435***	0.039**	0.052**	0.252***	0.079**	0.120**
Education (high)	0.366***	0.019**	0.101***	0.425	0.003	0.080**
Income (high)	0.384***	0.043**	0.074***	0.350***	0.038	0.135***
Digital skill (high)	0.368***	0.076***	0.114***	0.369***	0.027	0.040
ADAS (yes)	0.435***	0.028	0.037	0.345***	0.030	0.120***
Lack of infrastructure (high)	0.435***	0.039**	0.052**	0.252***	0.079**	0.121***
Perceived safety infrastructure (high)	0.386***	0.016**	0.115***	0.365***	0.006	0.120***
Traffic density (high)	0.549***	− 0.017	− 0.090*	0.397**	0.015	0.127**
Crash (yes)	0.388***	0.034**	0.073***	0.361***	0.025	0.128***
Population density (high) [g]	0.428***	0.064***	0.068**	0.346***	0.013	0.082**
City (<50 k) [g]	0.395***	0.022	0.034	0.318***	0.042	0.185***
City (>500 k) [g]	0.485***	0.072*	0.064	0.239**	0.095*	0.051
Cycle paths (few) [g]	0.500***	0.022	0.066**	0.297***	0.054	0.028

βstd: Standardised regression coefficient, ***: p-value < 0.001, **: p-value < 0.05, *: p-value < 0.1; [g] refers to geographical data

influence and effort expectancy. The impact of the socio-demographic characteristics varies on behavioural intention. Behavioural intention increases with the increase of age. Also, on the one hand, people older than 60 and people with high digital skills are willing to use a Smart Pedelec. On the other hand, people with high education levels are less willing to use a Smart Pedelec. Gender has no impact on behavioural intention. Regarding safety-related factors, lack of infrastructure negatively influences people's intention to use a Smart Pedelec, while crashes positively impact behavioural intention. There is neither a positive nor negative impact considering the geographical dimensions of behavioural intention on Smart Pedelec.

All the UTAUT2 constructs on behavioural intention for the Smart Speed-Pedelec have a positive sign; however, only performance expectancy and hedonic motivation significantly impact behavioural intention, and there is no significant impact regarding the other variables.

4.5.2. Cross-country analysis

Table 11 presents the investigation of cross-country differences and shows that performance expectancy has the highest impact and is significant across all countries. It has the highest impact in Germany and the lowest in the Netherlands. Hedonic motivation shows no impact in Austria, while for the remaining countries, it strongly impacts behavioural intention. Perceived safety has a strong and positive impact on Germany, Belgium, and the Netherlands, while there is no significance in Austria and Greece. Social influence remains a strong and positive construct in behavioural intention in Austria, Greece and the Netherlands, while there is no significance in Belgium, and it is negative in Germany. Effort expectancy has a positive relationship in Austria and the Netherlands. Social status has

Table 10
Behavioural intention of Smart Pedelec and Smart Speed-Pedelec.

Variables	Smart Pedelec	Smart Speed-Pedelec
	βstd	βstd
Dependent variable: behavioural intention		
Performance expectancy	0.382***	0.448***
Effort expectancy	0.033**	0.059
Social influence	0.075***	0.053
Hedonic motivation	0.368***	0.330***
Social status	0.022	0.053
Perceived safety	0.121***	0.058
Gender (male)	− 0.003	− 0.032
Age	0.028**	− 0.004
Age (>60)	0.018*	0.024
Education (high)	− 0.019*	− 0.015
Income (high)	0.000	− 0.055
Technology (high)	0.018*	− 0.010
ADAS (yes)	− 0.004	0.017
Lack of infrastructure (high)	− 0.025**	− 0.023
Perceived safety of infrastructure (high)	0.001	0.015
Traffic density (high)	0.007	0.007
Crash (yes)	0.025**	0.022
Population density (high) [g]	0.002	0.011
City size (<50 k) [g]	− 0.002	0.009
City size (>500 k) [g]	0.000	− 0.016
Cycle paths (few) [g]	0.006	− 0.007

βstd: Standardised regression coefficient,***: p-value < 0.001, **: p-value < 0.05, *: p-value < 0.1, [g] refers to geographical data

Table 11
Multi-countries analysis of behavioural intention.

Variables	AT	BE	DE	GR	NL	ALL
	βstd	βstd	βstd	βstd	βstd	βstd
Dependent variable. behavioural intention						
Performance expectancy	0.433***	0.420***	0.451***	0.442***	0.378***	0.394***
Effort expectancy	0.127*	0.056	0.015	0.056	0.033*	0.037**
Social influence	0.156**	0.027	−0.054	0.100**	0.111***	0.080***
Hedonic motivation	0.127	0.228**	0.332***	0.311***	0.396***	0.356***
Social status	0.071	0.076*	0.076	0.046	−0.001	0.027
Perceived safety	0.071	0.188***	0.196**	0.028	0.111***	0.112***
Gender (male)	0.048	0.034	0.034	−0.003	−0.011	−0.003
Age	0.049	0.006	0.045*	0.042	0.008	0.022
Age > 60	0.051	−0.007	0.022	0.045	0.006	0.016*
Education (high)	0.036	−0.027	0.025	−0.030	−0.004	−0.017*
Income (high)	0.023	−0.014	−0.028	0.001	−0.006	−0.005
Digital skills (high)	0.101	−0.002	0.003	0.053*	0.015	0.015
ADAS (yes)	−0.021	−0.006	−0.036	−0.032	0.003	−0.002
Lack of infrastructure (high)	0.008	0.003	−0.017	−0.023	0.010	−0.013
Perceived safety infrastructure (high)	−0.033	−0.020	−0.39	0.043	−0.019	0.002
Traffic density (high)	−0.031	0.024	0.004	−0.047	0.005	0.007
Crash (yes)	0.026	−0.007	−0.001	0.067**	0.008	0.024**
Population density (high) [g]	−0.043	0.022	−0.011	−0.026	0.005	0.002
City size (<50 k) [g]	0.013	0.004	−0.030	0.005	0.016	0.001
City size (>500 k) [g]	−0.043	−0.008	0.034	0.003	0.004	0.003
Cycle paths (few) [g]	0.042	0.021	−0.029	0.001	0.004	−0.004

βstd: Standardised regression coefficient,***: p-value < 0.001, **: p-value < 0.05, *:p-value < 0.1, [g] refers to geographical data

a positive but weak influence on behavioural intention in all countries except the Netherlands.

Socio-demographic characteristics indicate that high income has a negative impact on German respondents, while the increase in age has a positive and significant impact. High digital skills positively impact the behavioural intention of the Greek sample.

For the safety-related effects, people involved in crashes have a positive intention about the Smart e-bike in Greece, and there is no effect on the other countries. For the rest of the countries, there are various positive impacts in Austria and the Netherlands and negative ones in Germany and Belgium; however, these effects are not significant. To conclude, there is no significance for the geographical factors, such as city size, low availability of cycle paths and population density.

5. Discussion

In the previous sections, the results revealed several insights regarding factors that affect the behavioural intention to use a Smart e-bike. This section discusses the results, their implications, and the contribution of this study to the literature. Table 12 summarises the hypotheses and sub-hypotheses that were tested.

5.1. Smart e-bike implications and contribution of this study

With the increased living cost and the trend of electrification and more environmentally friendly transport modes, the number of people who switch from cars to e-bikes is increasing (de Haas and Huang, 2022; Shimano, 2022). While this is desirable since it reduces travel costs, emissions and congestion in cities, the number of crashes is increasing (Haustein and Møller, 2016; Kapousizis et al., 2022). Therefore, it was essential to investigate the user acceptance of the emerging Smart Pedelec and Speed-Pedelec, which can influence cycling safety and comfort. The scope of this paper was to understand the extent to which e-bike users may consider using smart bicycle technologies. Note that we are not making an argument that cyclists should use these technologies. By presenting these findings, we aim to provide empirical insights to stakeholders and policymakers. While important, the assessment of our study countries' driving/cycling culture was not within the scope of our analysis. Also, while not all countries worldwide allow speed Pedelecs, interested stakeholders might focus only on the Pedelecs' results of this study.

From the six hypotheses tested, five were supported (Performance expectancy, Effort expectancy, Social influence, Hedonic motivation, and Perceived safety), with performance expectancy, hedonic motivation and perceived safety having a strong and positive relationship with users' intention to use a Smart e-bike in the aggregated data sample. A comparison of the findings with those of other studies confirms that these constructs play a significant role in behavioural intention of new technologies (Kapser et al., 2021; Venkatesh et al., 2012). This is also congruent with previous studies on the acceptance of shared bicycle systems and e-bikes (Jahanshahi et al., 2020; Simsekoglu and Klöckner, 2019a; Wolf and Seebauer, 2014). Specifically, performance expectancy has a higher impact on behavioural intention to buy and use a Smart e-bike, indicating that the usefulness of the Smart e-bike is the key element.

Hedonic motivation also has a strong and positive impact on behavioural intention, which indicates that the Smart e-bike offers fun and enjoyment to potential users, affecting their intention to use it. In addition, perceived safety is the third highest construct that affects behavioural intention, which means that behavioural intention to use and buy a Smart e-bike increases with the safety improvement offered by the Smart e-bike. Social influence also positively impacts behavioural intention, which indicates that the pressure of relatives and family members influences potential users' intention towards Smart e-bikes. Effort expectancy has a moderate positive impact on behavioural intention, in agreement with other studies about AVs (Curtale et al., 2021; Nordhoff et al., 2020a), hence the Smart e-bike needs to be simple in use to be acceptable to people. Finally, social status has a positive impact, although it is not significant. In other words, some people think that with the Smart e-bike, they could be part of a group or prove their social status.

We also controlled the model with numerous sub-hypotheses considering socio-demographic, infrastructural, geographical, and safety-related variables. We found that behavioural intention to use Smart e-bikes increases, especially among people involved in crashes and people older than 60 years. A possible explanation might be that most older people own e-bikes and are prone to crashes

Table 12
Hypotheses and sub-hypotheses tested.

Hypothesis	Path and proposed effect	AT	BE	DE	GR	NL	ALL
H1	PE → BI (+)	S	S	S	S	S	S
H2	EE → BI (+)	S	–	–	–	S	S
H3	SI → BI (+)	–	S	–	S	S	S
H4	HM → BI (+)	–	S	S	S	S	S
H5	ST → BI (+)	–	S	–	–	–	S
H6	PS → BI (+)	–	S	S	–	S	S
H7a	Gender (male) → BI (+)	–	–	–	–	–	–
H7b	Age → BI (+)	–	–	S	–	–	–
H7c	Age (older than 60) → BI (+)	–	–	–	–	–	S
H7d	Education (high) → BI (+)	–	–	–	–	–	–
H7e	Income (high) → BI (+)	–	–	–	–	–	–
H8a	Digital skills (high) → BI (+)	–	–	–	S	–	–
H8b	ADAS (yes) → BI (+)	–	–	–	–	–	–
H9a	Lack of infrastructure → BI (+)	–	–	–	–	–	–
H9b	Perceived safety infrastructure (high) → BI (+)	–	–	–	–	–	–
H9c	Traffic density (high) → BI (+)	–	–	–	–	–	–
H9d	Crash (yes) → BI (+)	–	–	–	S	–	S
H10a	Population density (high) → BI (–)	–	–	–	–	S	–
H10b	City size (>50 k) → BI (+)	–	–	–	–	–	–
H10c	City size (>500 k) → BI (+)	–	–	–	–	–	–
H10d	Few cycle paths → BI (–)	–	–	–	–	–	–
*H*11	Countries are heterogenous → BI (≠)	S	S	S	S	S	S
S: Supported							

(de Haas and Huang, 2022; Fishman and Cherry, 2016; Statistics Netherlands (CBS), 2021). Furthermore, the lack of cycling infrastructure negatively influences behavioural intention to use Smart e-bikes which supports the requirement for cycling infrastructure to attract more people to cycling (Buehler and Pucher, 2021; Nikitas et al., 2021). Lastly, we controlled for differences in behavioural intention among e-bike users and participants willing to buy one; however, we did not capture any significant difference among these groups.

Regarding the Smart Pedelec, all constructs except for social status are positive and significantly influence behavioural intention, with the strongest being performance expectancy, hedonic motivation and perceived safety. In addition, older age, involvement in a crash and familiarity with technology are the variables with the strongest positive influence on behavioural intention to use Smart Pedelec. On the contrary, the perceived lack of cycling infrastructure and high education have the strongest negative influence. In relation to the Smart Speed-Pedelec, only performance expectancy and hedonic motivation positively and significantly influence behavioural intention. The rest of the UTAUT constructs have a positive impact, even though they are not significant. No additional variables significantly influence behavioural intention to use Smart Speed-Pedelec either positively or negatively. Several factors could explain this difference between Smart Pedelec and Smart Speed-Pedelec: first, the small sample size for Smart Speed-Pedelec; second, Speed-Pedelecs are a special category of transport mode and are mainly used by middle age commuters who might tend to feel safe and capable (Vlakveld et al., 2021). Due to these factors, Speed-Pedelec users might find the variables which comprise the constructs of performance expectancy and hedonic motivation more important than the rest; third, that generally people keep a relatively neutral attitude toward emerging transport modes (Van den Steen et al., 2019). However, since no clear reason exists, further investigation is needed to draw conclusions.

The cross-country comparison allowed us to understand better the differences between countries that vary in cycling rates and cycling infrastructure towards the Smart e-bike. More specifically, the results of the cross-country analysis highlight some key elements. Performance expectancy is a strong and positive predictor for Austria, Belgium, Germany and Greece, while hedonic motivation is higher and stronger in the Netherlands, followed by performance expectancy and social influence. This is expected due to the presence of a higher cycling rate in the Netherlands than the other countries (Goel et al., 2021). The impact of effort expectancy in Austria is stronger than in the other countries but is still lower than the other constructs. The reason for this is not clear, but it may have something to do with the distribution of the respondents in Austria since 50 % of them live in Vienna and might be familiar with new mobility technologies. Perceived safety positively and significantly impacts behavioural intention toward the Smart e-bike in Belgium and the Netherlands; this could probably be due to the dense cycling infrastructure and the high penetration of e-bikes in these countries. In contrast, perceived safety has no significant impact in Austria and Greece. A possible explanation is that Austria and Greece have fewer cycle paths than the other countries. Social status is slightly negative in the Netherlands, probably due to the high penetration rate of e-bikes and cycling (de Haas and Huang, 2022; Goel et al., 2021). High income has mainly negative and no significant impact across the countries. This relationship may partly be explained by the fact that high income people are described with high car ownership (Buehler et al., 2016). High digital skills and experience of crashes positively impact behavioural intention in the Greek sample.

5.2. Theoretical implications

From a theoretical point of view, this study is the first and contributes to existing knowledge investigating user acceptance of the Smart e-bike by utilising an extension of the UTAUT2. Thus, while UTAUT2 is one of the most comprehensive psychological frameworks so far, adjustments are needed to capture the different objectives of new, state-of-the-art technologies better (Kapser et al., 2021; Nordhoff et al., 2020a). The present study shows that the UTAUT2 model can be applied to new smart cycling technologies and explain users' behavioural intentions by integrating new constructs, such as perceived safety. Moreover, this study confirms that perceived safety is an additional essential factor which explains behavioural intention to use Smart e-bikes.

An important takeaway of this study is that while the UTAUT2 and SEM are widely used in the transportation domain, making comparisons among groups is not well-established in the literature. The analysis of the measurement invariance undertaken in this paper contributes to the literature by extending our knowledge of multigroup comparisons in the transportation domain. Studies in transportation typically do not examine measurement equivalence among cross-country or multigroup analyses, creating uncertainty about whether comparing the latent variables across groups/countries measures the same objects. This study shows that MI is essential in multigroup analysis to ensure meaningful group comparisons. We obtained scalar invariance for the smart Pedelec and smart Speed-Pedelec comparison and metric invariance for the countries comparison, which are satisfactory levels to allow comparisons among groups. This allowed us to proceed properly with the multigroup analysis and draw firm conclusions among countries. Finally, the model used in this study indicates that different psychological factors better fit and explain behavioural intention due to the cultural differences among the selected countries. Thus, the cross-cultural comparison allowed us to examine the differences between countries and better understand the factors influencing users' acceptance of the Smart e-bike.

5.3. Practical implications

From the practical point of view, this study shows that performance expectancy was the most important construct of behavioural intention across most countries, followed by hedonic motivation and perceived safety. Thus, improving the characteristics of the Smart e-bike related to these constructs will be beneficial in promoting it. However, our analysis found variability among the constructs that impact users' intentions between countries, hence, it is important to interpret the results carefully since different factors affect the behavioural intention to use and buy a Smart e-bike. For instance, performance expectancy was a significant construct in all countries, meaning that participants in this study expect that the Smart e-bike will enhance their lives. This implies that, bicycle manufacturers and designers should pay more attention to users' needs in designing and promoting Smart e-bikes compared to users' regular e-bikes. Hedonic motivation strongly influences the behavioural intention to use and buy the Smart e-bike in all countries but not in Austria. Hence, improving the Smart e-bike's characteristics, which make it more enjoyable and pleasurable, would be an advantage in all countries except Austria. Social influence was found positive in Austria, Greece, and the Netherlands; therefore, promoting the Smart e-bike using social pressure regarding its positive features would positively influence its promotion in these countries. Perceived safety influences Belgium and Dutch respondents, indicating that the Smart e-bike has a higher acceptance as it is perceived as safer. Given the significant strength of the perceived safety construct in these countries, it may be beneficial for policymakers to foster the Smart e-bike as a comfortable and safe mode of travel. Some countries had particularly low levels of perceived safety, e.g., Greece. Smart e-bikes alone cannot meet the fundamental safety needs of cyclists. The provision of safe infrastructure and other steps to ensure the safety of vulnerable road users is needed as a prerequisite. However, providing safer infrastructure may encourage cycling uptake, and for some, smart e-bikes may still be attractive. Policymakers may want to promote smart e-bikes. Furthermore, effort expectancy has a lower impact on behavioural intention; hence, the ease of use of the Smart e-bike is a principal factor for its promotion. Policymakers should consider the context of areas in defining where and for whom it may be appropriate to promote the smart e-bike. For instance, in the Netherlands, a high proportion of crash fatalities lay to cyclists older than 75 (Statistics Netherlands (CBS), 2023). Thus, promotion in this group might be beneficial since people will continue to use active travel modes with extra safety features.

Potential Smart e-bike users need to be convinced about the performance of a bike before they consider buying one. This can be done by developing and testing prototypes, allowing potential users to test the Smart e-bike's features and realise its usefulness. For this, a collaboration between governments and bicycle manufacturers could benefit society, first by providing help for field trials and later by subsidising such safety functionalities. Furthermore, the results of this study suggest that policymakers should consider the national context to better decide which features of Smart e-bikes meet local needs and, based on these, decide which functionalities might be appropriate to be promoted.

To conclude, encouraging the acceptance of the Smart e-bike and other smart technologies on bicycles can benefit society and improve sustainability in cities since such systems can support users and reduce crash risk (Kapousizis et al., 2022; Oliveira et al., 2021). This requires governments' and municipalities' support to prioritise the development of digital infrastructure, an underlining factor of performance expectancy related to the Smart e-bike's functionalities, such as B2I communication. Also, we recommend countries lacking cycling infrastructure to prioritise improvements in physical infrastructure since the lack of infrastructure is a negative factor in users' intention to use the Smart e-bike. Thus, the introduction of Smart e-bikes should go hand in hand with the development of dedicated cycling infrastructure.

5.4. Limitations and future work

This study investigated users' acceptance of the Smart e-bike in a hypothetical setting, hence users' hands-on experience with these bicycles is not yet captured. This is a common limitation with studies exploring the user acceptance of emerging technologies. In addition, the sample of this study comes mainly from e-bike users and people willing to buy one. While we chose to get more reliable results at this time, we recommend further research to survey the entire population and investigate whether such technologies can influence people who do not cycle to switch to e-bikes. Also, the sample size differs among the countries, which might impact the results for the cross-country comparison. Furthermore, this study investigates the behavioural intention to use a Smart e-bike, hence, the willingness to pay for such technologies is still unknown. This is an important factor for investigation since it can determine the penetration rate of such bicycle features and help designers build more suitable ones. In future work, we will examine if stated choice experiments will help to better understand people's preferences regarding different smart e-bike functionalities. In addition, since the Smart e-bike examined here is not on the market yet, it is relevant for differences between ex-ante preferences and user acceptance after riding smart e-bikes to be examined in future field trials and/or simulation environments. Human-machine interaction is another point for further research to prevent users from getting distracted by such systems, potentially increasing crash risks. Hence, designing the Smart e-bike while considering the communication of the systems with the users and under different traffic situations is a key element in the introduction of Smart e-bikes. While this study focused on users' acceptance of bicycle technologies, the automotive industry also examines Bicycle-to-vehicle communication. This is one of the many scenarios for improving the future of urban transport, however, the arguments for the digital conspicuity of other road users through devices such as smart e-bikes should be stronger. Many studies have investigated this, which could further improve cycling safety, and there is room for further research on user acceptance and willingness to pay on this topic. Lastly, another potential avenue for future research is to investigate to what extent factors such as the topographical and climate characteristics of these countries influence users' acceptance of Smart e-bike.

6. Conclusion

This study provides the first extensive assessment of behavioural intention to use the Smart e-bike as a potential solution to reduce e-bike crashes and improve comfort. We employed a comprehensive tailor-made framework based on the UTAUT2 to analyse the survey data collected from five European countries. Our key findings are summarised below:

- Six psychological constructs were tested, however, the results prove that only three of them (performance expectancy, hedonic motivation, and perceived safety) significantly influence behavioural intention to use Smart e-bikes in the aggregate sample. Among other variables, age and people who had experienced crashes have a positive and significant effect on behavioural intention.

- The cross-country analysis clearly indicates that the constructs influencing behavioural intention on Smart e-bikes are heterogeneous across the five countries. This supports the idea that different psychological constructs play a key role among countries.
- Due to inconsistencies in behavioural intention across countries, customised actions per country must be taken to promote Smart e-bikes.

In addition, we further examined the behavioural intention to use Smart e-bikes in the subdivision of Smart Pedelec and Smart Speed-Pedelec in the aggregated sample:

- The multigroup analysis revealed that behavioural intention for Smart Pedelec is stronger compared to Smart Speed-Pedelec, with five constructs supporting this.
- It is evident that both performance expectancy and hedonic motivation are dominant positive constructs. However, even though more constructs influence behavioural intention for the Smart Pedelec, these are the only constructs affecting the intention to use the Smart Speed-Pedelec.

The findings offer new insights into the deployment of new technologies on e-bikes and will be of interest to different stakeholders, such as policymakers and industry. Industry can integrate these insights to develop and design such innovative systems, and policymakers can modernise traffic lights and implement digital infrastructure to achieve B2I communication to foster Smart e-bikes penetration rate (Kapousizis et al., 2022).

CRediT authorship contribution statement

Georgios Kapousizis: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rumana Sarker:** Writing – review & editing, Validation, Conceptualization. **M. Baran Ulak:** Conceptualization, Writing - review & editing. **Karst Geurs:** Conceptualization, Writing – review & editing.

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 A. Heterotrait-Monotrait ratio correlation

	PE	EE	SI	ST	HM	PS	BI
PE							
EE	0.363						
SI	0.644	0.231					
ST	0.565	0.208	0.597				
HM	0.733	0.421	0.594	0.615			
PS	0.637	0.394	0.552	0.499	0.654		
BI	0.750	0.401	0.634	0.579	0.744	0.670	

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