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Transitional behavioral intention to use autonomous electric car-sharing services: Evidence from four European countries

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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

Electric car-sharing services (ECS) have been promoted as a solution to combat negative urban mobility externalities and are expected to be facilitated by fleets of autonomous vehicles. There is little evidence regarding the behavioral intention to use autonomous ECS (AECS), especially on the transition from using ECS. This paper investigates the behavioral intention to use AECS using psychological constructs partially from the extended unified theory of acceptance and use of technology (UTAUT2) and an additional one expressing safety concern. A novel behavioral intention model is presented to capture the transitional behavioral intention to use two adjacent generations of sharing mobility services. Results of structural equation models applied to a survey sample of 2154 respondents from France, Italy, Netherlands, and Spain show that the introduction of AECS is very likely to be accepted by ECS users. Hedonic motivation is found to be a much stronger predictor of behavioral intention to use AECS as opposed to safety concern, while performance expectancy and social influence are strong drivers of intention to use ECS and have indirect effects on the intention to use AECS. Multigroup analysis indicates heterogeneous behavioral intention across countries. The multi-faceted empirical results generate insights into the deployment and management of AECS in various contexts.

1. Introduction

In the last century, the urbanization process and improved quality of life in cities have been accompanied by an explosive increase in car ownership and use for urban mobility. The majority of private cars still use gasoline or diesel fueled internal combustion engines (ICE), whose intensive use is associated with negative externalities, such as traffic congestion, carbon emission, noise, and space scarcity for parking. The challenge for urban mobility managers and operators is to satisfy people's mobility needs without sacrificing the livability and sustainability of cities.

1.1. Background

One promising solution to tackle these urban problems is the wide adoption of electric car-sharing services (ECS), referring to short-term rentals of electric cars for a proportion of urban trips. The standard ICE-based car-sharing services (CS) date back to the 1940s. Their use had been quite limited until the beginning of the 2000s (Shaheen and Cohen 2007) given that the constraints provided by the

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round-trip station-based scheme caused difficulties in reaching a large user base. The first ECS date back to the 1990s in the US and Europe (Shaheen et al. 2013; Wappelhorst et al. 2014). Compared to ICE-based cars, electric cars had inferior performance in terms of lower driving range and density of charging station locations (Thøgersen and Ebsen 2019). These aspects increased the operational costs of running ECS and caused inconvenience to users. ECS remained unpopular in the 2000s and experienced a renaissance only in the last decade. Their adoption has recently been spurred by the introduction of more flexible one-way station-based or free-floating sharing schemes, advanced information systems to improve convenience and reduce transaction costs, and cutting-edge vehicular technologies (Becker et al. 2017; Wang and Liao 2021).

With the rapid development of vehicle automation technologies, autonomous vehicles (AVs) are expected to affect the supply of ECS in the near future. Several studies argued and showcased how shared AVs potentially contribute to reductions in travel distances and generalized travel costs due to the capability of AV self-relocations and other advantages (Fagnant and Kockelman 2015, 2018; Li and Liao 2020). Particularly, Pernestål and Kristoffersson (2019) found in their reviews of 26 simulations that only those including shared AVs showed a reduction in travel distances. Sheppard et al. (2021) demonstrated in a US-wide simulation that replacing 9% of the current fleet with AVs could reduce greenhouse gas emissions by 70%. Thus, it can be envisioned optimistically that the wide adoption of AVs in ECS will have both economical and environmental benefits. However, thus far, it is unclear about the degree of acceptance from end-users and the transitional behavioral intention from ECS to ECS with AVs (AECS), which lies in the intersection between the AVs and ECS domains (Fig. 1).

The most difficult and commonly expressed issue with the study of AV acceptance, whether or not coupled with CS or ECS, is that AVs remain unavailable to the public and most respondents have no real experience of using AVs. While the development of new technologies is predictable, the acceptance and the psychological drivers leading people to use them are usually uncertain (Martínez-Díaz et al. 2018). Therefore, there is a necessity of studying the psychological factors affecting people's intentions to use the new mobility services.

1.2. Literature review

Increasing research has been conducted on the demand side of sharing mobility since it only serves a niche market (e.g., Bardhi and Eckhardt 2012). About the user profile of ECS, early adopters are usually males, young, highly-educated, and live in city centers (Becker et al. 2017; Efthymiou et al. 2013; Prieto et al. 2017). As for user preferences, ECS are found to be more attractive than standard CS (Cartenì et al. 2016) due to higher environmental friendliness and stronger social acceptance (Burghard and Dütschke 2019). In addition, travelers, if adequately incentivized, may adapt mode and destination choice favoring sharing mobility (Curtale et al., 2021a; 2021b). Only a few studies investigate the psychological factors affecting the behavioral intention to use ECS. In a study conducted in Seoul (South Korea), Kim et al. (2015) showed that the main drivers of using ECS are both economic (e.g., travel cost savings or reduced maintenance concerns) and social (e.g., making a good impression on others). Tran et al. (2019), in a survey conducted in Dalian (China), found that people's intentions to use ECS can be explained by performance expectancy, effort expectancy, hedonic motivation, and familiarity. Curtale et al. (2021a; 2021b), in a recent study conducted in the Netherlands, identified performance expectancy, social influence, and personal attitude as the main predictors of intention to use ECS.

Regarding the user acceptance of AVs, existing studies applied behavioral theories in different contexts to investigate the decision-making process behind it. For example, using an adapted version of the unified theory of acceptance and use of technology (UTAUT, Venkatesh et al. 2003), Madigan et al. (2017) concluded that hedonic motivation is the strongest driver of intention to use AVs. Lavieri and Bhat (2019) investigated individuals' current choices and future intentions to share rides in an AV and found that additional travel

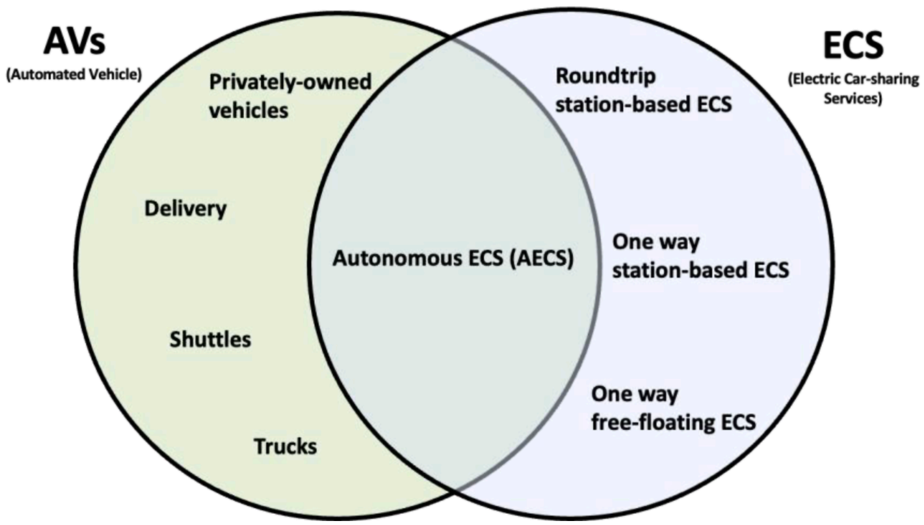

Fig. 1. The intersection between AVs and ECS.

time due to other passengers in the vehicle could be more problematic than the other passengers themselves. Asmussen et al. (2020) found that socio-demographic characteristics had varying impacts on the latent factors used to evaluate potential interest in AV adoption, and concluded that it might be crucial to include the habits and consumption motivations of different socio-demographic groups. Yuen et al. (2020) used the theory of planned behavior (TPB) and found that attitude has a huge effect on public acceptance of AVs. Kaye et al. (2020) combined TPB and UTAUT to assess a prior acceptance of AVs and found that attitude, control, and performance expectancy have significant but varying impacts. In the context of using AVs during vacations, Ribeiro et al. (2021) found that social influence was a significant determinant related to perceived risks of using AVs, trust was a determinant of performance expectancy, and emotions are the strongest determinant of the intention to use AVs. A list of studies investigating the psychological drivers affecting the behavioral intention to use ECS and AVs is shown in Table 1.

1.3. Research objective

The above studies provide valuable insights into the unobservable factors affecting behavioral intention ECS or AVs separately. However, little is known on how the introduction of AVs in ECS fleets affects people's behavioral intentions to use AECS and to what extent the intention varies across spatial contexts. To obtain integral evidence of behavioral intention to use the future of mobility, the present study aims at three contributions. First, we apply and extend one of the most established behavioral theories in the information system field for technology acceptance, UTAUT2 (descendent of UTAUT, Venkatesh et al. 2012), to analyze the behavioral intention to use AECS with Level-5 AVs (SAE International 2014). The conceptual model adopts constructs partially from the UTAUT2 and an additional one capturing safety concern. Second, we study the transitional behavioral intention to use ECS and AECS. The model involves a decent alignment of relevant psychological constructs for the sake of parsimony. Third, we execute multigroup analyses for the comparison of behavioral intention in four European countries (France, Italy, Netherlands, and Spain), where CS or ECS have a noticeable user base and the readiness for AVs is relatively high (KPMG 2020). The results from structural equation models applied to a large survey sample show that AECS would be highly accepted by ECS users. Alongside performance expectancy and social influence, hedonic motivation plays a pivotal role in the intention to use AECS, while safety concern is not a significant deterrent for all contexts.

The remainder of this paper is organized as follows. Section 2 introduces the research framework, including the conceptual model and hypotheses. Section 3 presents the survey, the sample composition, and the analysis method. Section 4 explains the main results and Section 5 discusses the relevance with the extant literature and the managerial implications for service operators. Finally, Section 6

Table 1
Studies investigating psychological drivers of ECS and AVs respectively.

Reference	Transport mode	Country	Framework	Main factors studied	Main findings
Kim et al., (2015)	ECS	South Korea	List of items investigating user satisfaction	SEV, BFP, RCD, SEP	SEV(+), BFP(+), RCD(+), SEP(+)
Burghard & Dütschke (2019)	ECS	Germany	DOI	COM, EU, OBS, SN, TRI	COM(+), TRI(–)
Tran et al., (2019)	ECS	China	UTAUT2	PE, EE, SI, HM, FAM	PE(+), EE(+), HM(+), FAM(+)
Curtale et al., (2021)	ECS	Netherlands	UTAUT2	PE, EE, SI, AE, AT, TR	PE(+), EE(+), SI(+), AE(+), AT(+), TR(+)
Madigan et al., (2017)	AVs (shuttles)	Greece	UTAUT2	HM, PE, SI, FC, EE,	HM(+), PE(+), SI(+), FC(+)
Yuen et al., (2020)	AVs (privately-owned)	South Korea	TPB	AT, HM, BC, RA, SN, CPL, COM	AT(+), HM(+), BC(+), RA(+), SN (+), CPL(–), COM(+)
Kaye et al., (2020)	AVs (privately-owned)	Australia, France, Sweden	TPB, UTAUT2	PEK, AT, SN, PBC-cap, PBC-cont, PE, EE, FC	AT(+), SN(+), PBCcap(+), PE+, PBCcont(+in AU), EE(+in FR), PEK(– in AU)
Kettles & Van Belle (2019)	AVs (privately-owned)	South Africa	UTAUT2	PE, EE, SI, HM, TS, RK	PE(+), EE(+), SI(+), HM(+), TS(+), RK(+)
Ribeiro et al (2021)	AVs (privately-owned)	USA	CAT, AIDUAM	PE, SI, HM, TR, PR, EMO	PE(+), HM(+), TR(+), PR(–), EMO (+)
Kapser and Abdelrahman (2020)	AVs (delivery)	Germany	UTAUT2	PE, EE, SI, FC, HM, PR, PS	PE(+), SI(+), FC(+), HM(+), PR(–), PS(–)
Kapser et al (2021)	AVs (delivery)	Germany	UTAUT2	PE, SI, HM, PR, PS, TT, INO	PE(+), SI(+), HM(+), PR(–), PS(–), TT(+), INO(+)

Abbreviations. *Framework*: AIDUAM = Artificially Intelligent Device Use Acceptance Model, CAT = Cognitive Appraisal Theory, DOI = diffusion of innovation, TPB = Theory of Planned Behaviour, UTAUT = Unified Theory of Acceptance and Use of Technology.
Main factors studies: AE = anxiety-free experience, AT = attitude, BFP = Booking & Fee & Payment, COM = compatibility, CPL = complexity, EE = effort expectancy, EMO = emotions, EU = ease of use, FC = facilitating conditions, FAM = familiarity, HM = hedonic motivation, INO = innovativeness, OBS = observability, PBCcap = perceived behavioral control capability, PBCcont = perceived behavioral control controllability, PE = performance expectancy, PR = perceived risk, PS = price sensitivity, RCD = Renting & Charging & Driving, RK = resources and knowledge, SEP = social and economic perspective, SEV = shared EVs, SI = social influence, SN = social norm, TR = trust, TRI = trialability, TT = trust in technology, TS = trust in safety.
Main findings: +/– = positive or negative impact, AU = Australia, FR = France.

concludes the paper and points out possibilities for future work.

2. Research framework

This section presents the conceptual framework for investigating the behavioral intention to use AECS in multiple study areas. Four European countries (i.e., France, Italy, Netherlands, and Spain) were selected due to the relatively high readiness for AVs but different preferences and penetrations of sharing mobility. CS were introduced in the Netherlands in 1973 by the Witkar company, which did not have much success and stopped offering the services in 1988 (Nijland and van Meerkerk 2017). In the 1990s, CS started to rise slowly again and received a boost in 2015 after the Green Deal between the central government and local public authorities (Münzel et al. 2019). In France, CS were introduced in the 1990s, with its adoption increasing significantly after 2010 when the Law on Environment created a national label legalizing the use of parking spaces specifically for CS (d'Arcier and Lecler 2019). In Italy, the first CS were introduced in 2001 after an initiative of the Ministry of Environment, and free-floating CS arrived in 2013 (Rotaris 2021). In Spain, CS started to operate in 2005 (Loose 2010) and recorded a rapid increase, especially in big cities (Silvestri et al. 2018). The four countries are also characterized by significantly different car ownership (EAMA 2021) and travel habits, such as different confidence in sharing services and attitudes towards public transportation and active modes (Copenhagenize 2019; Prieto et al. 2017; Minelgaitė et al. 2020).

2.1. Conceptual model

To explain the behavioral intention to use AECS, we adopt the most important factors of the UTAUT2 given the matureness and wide applications for studying user acceptance (Tamilmani et al. 2021). To incorporate the transition from using ECS, we consider the uses of ECS and AECS in an integrated theoretical framework. The UTAUT2 includes core variables that can also explain the acceptance of technology in other domains. One of its limitations is the lack of relevant variables in specific applications. Several studies, classified as "UTAUT2 extensions", aim at including relevant constructs in a structural equation model (SEM) to UTAUT2 applications that were missing in the original theory. Interested readers might refer to the work of Evermann & Tate (2009), who show how to build a new theory in SEM, and Weber (2012), who present the framework and criteria to develop high-quality theories by combining existing ones. Thus, we formulate a conceptual model that includes psychological constructs taken from the UTAUT2 and an additional one addressing safety concerns, adapted from other empirical studies on the use of AVs (Bonnefon et al. 2016; Kapser and Abdelrahman 2020; Madigan et al. 2017; Ribeiro et al. 2021). Because of the common and different features of ECS and AECS, we strategically formulate the relationships between the factors to form a succinct but substantive model. Performance expectancy, effort expectancy, and social influence are considered the predictors of intention to use ECS because we expect high reliability of these factors for an already diffused technology and service. Hedonic motivation is considered for both ECS and AECS due to the strong evidence of its importance for using ECS and AVs in separate studies. We expect that hedonic motivation has lower impacts on using ECS due to a lower degree of technological innovation in ECS compared to that in AECS, meaning that AECS might be considered more exciting because of its relative novelty. Safety concern is considered a predictor of intention to use AECS since the potential for increased safety due to vehicle automation has been widely publicized. Behavioral intention to use ECS is included as a predictor to use AECS to model the degree of transitional behavioral intention. This structure compensates for the omission of other psychological factors of the

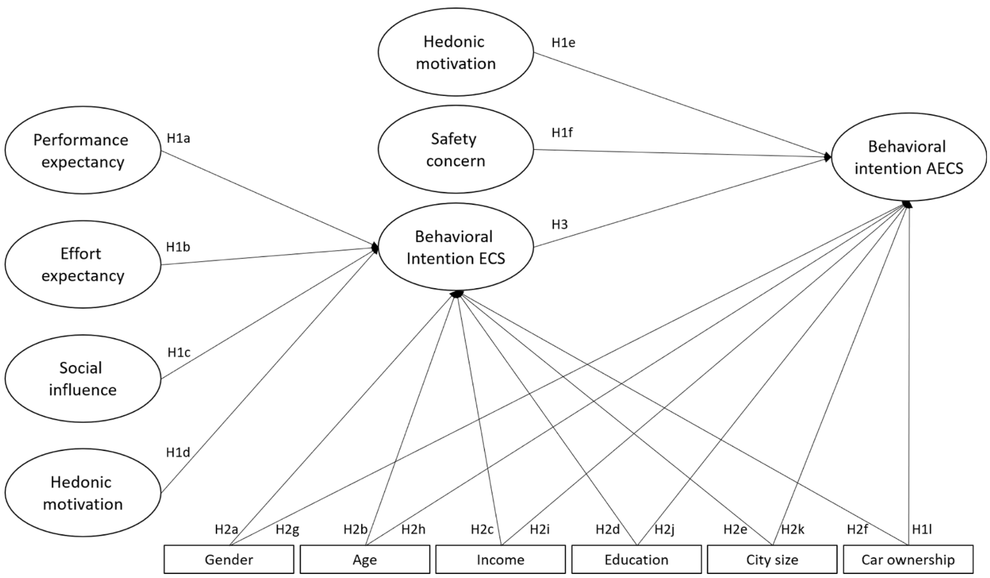

Fig. 2. Conceptual model (arrows indicate directed effects).

original UTAUT as predictors to use AECS. Six socio-demographic variables are also included to test the moderating effects for using ECS and AECS, respectively. To offer a holistic view, we performed the same form of analysis simultaneously in multiple countries and show the disaggregated country-level analysis as well as an analysis of all respondents together. In this way, we can identify the cross-country and country-specific drivers of behavioral intention to use AECS. A graphical representation of the conceptual model is depicted in Fig. 2.

As shown, the behavioral intention to use ECS and AECS is predicted by the above-mentioned psychological constructs as well as socio-demographic characteristics. The impacts of socio-demographic characteristics on behavioral intention are considered direct and/or mediated by psychological constructs. Other constructs of the UTAUT2 (i.e., price value, habit, and facilitating conditions) are not included as we observe little relevance of them to predict the behavioral intention to use AECS, which are not available yet to the public. Excluding those variables of UTAUT2 in studies investigating behavioral intention is not an uncommon practice in transport studies, as shown by Kettles & Van Belle (2019), Tran et al. (2019), Curtale et al. (2021a; 2021b), and Kapser et al. (2021). Specifically, price value and habit, which in the UTAUT2 refer to the perception of fair prices and repeated uses respectively, are not applicable to our case of study given the absence of AECS in the market. Although price value is a relevant variable for behavioral intention, several authors applying UTAUT2 to autonomous vehicles excluded it (Kaye et al. 2020; Kettles & Van Belle 2019; Madigan et al., 2017; Ribeiro et al. 2021). To the best of our knowledge, the only studies considering a dimension for price are Kapser and Abdelrahman (2020) and Kapser et al. (2021), who studied price sensitivity instead of price value. In several studies, facilitating conditions presented no significant effect on the use of AVs in France, Greece, and Sweden (e.g., Kaye et al. 2020; Madigan et al. 2017). Finally, facilitating conditions and habit in the original formulation of UTAUT2 tend to be more relevant predictors of actual use rather than behavioral intention (Venkatesh et al. 2003; 2012), which is not investigated in this study either. Taking these aspects into account, we exclude price value, habit, and facilitating conditions to maintain a concise theoretical model. The hypotheses of the relationships between the constructs and moderating variables, represented by notations in Fig. 2, are discussed below.

2.2. Hypotheses

We investigate the behavioral intention to use ECS and AECS with four hypotheses. Every hypothesis is formulated referring to a domain (e.g., psychological constructs or socio-demographic variables). A hypothesis may correspond to one main hypothesis and several sub-hypotheses explicitly stated when needed. The core variables of the UTAUT and UTAUT2, namely performance expectancy, effort expectancy, and social influence have been found as significant drivers of behavioral intention in various applied studies in the transport field (Curtale et al. (2021a; 2021b); Fleury et al. 2017; Kapser and Abdelrahman 2020; Kapser et al. 2021; Leicht et al. 2018; Madigan et al. 2017; Ribeiro et al. 2021; Tran et al. 2019). One of the common findings is that performance expectancy has a positive impact on behavioral intention to use ECS (Curtale et al. 2021a; 2021b; Tran et al. 2019) and AVs (Kapser and Abdelrahman 2020; Leicht et al. 2018; Madigan et al. 2017; Ribeiro et al. 2021). Effort expectancy has been shown to have significant impacts in France for corporate CS (Fleury et al. 2017) in China for ECS (Tran et al. 2019) and South Africa for AVs (Kettles & Van Belle 2019). Social influence has significant impacts in the Netherlands for ECS (Curtale et al., 2021a; 2021b), and South Africa (Kettles & Van Belle 2019), and Germany (Kapser and Abdelrahman 2020; Kapser et al. 2021) for AVs. Hedonic motivation is a significant predictor of behavioral intention for ECS in China (Tran et al. 2019), AV delivery in Germany (Kapser and Abdelrahman 2020), use of automated road transport systems in Greece (Madigan et al. 2017), and AVs in the USA (Ribeiro et al. 2021) and South Korea (Yuen et al. 2020). Safety concern, which is not part of a specific behavioral theory, has been empirically considered a deterrent of using AVs in several studies (Kapser and Abdelrahman 2020; Kyriakidis et al. 2015; Ribeiro et al. 2021). Madigan et al. (2017) also discussed the issue of safety and the increasing relevance since AVs testing nowadays moves toward unsupervised conditions (i.e., with no operator on board to take control of the vehicle). Based on the previous evidence, the first hypothesis of our conceptual model is the following.

Hypothesis 1. *Psychological factors have significant impacts on behavioral intention to use ECS and AECS, of which sub-hypotheses are shown in* Table 2.

Several studies investigated the role of socio-demographic characteristics in affecting people's behavioral intentions to use CS and ECS. For example, males were found to have a higher intention to use CS and ECS (Becker et al. 2017; Cartenì et al. 2016; Prieto et al. 2017; Curtale et al., 2021a; 2021b). A higher intention is also associated with younger generations (Cartenì et al. 2016; Efthymiou et al. 2013; Prieto et al. 2017), highly-educated people (Becker et al. 2017; Prieto et al. 2017), people living in city centers (Prieto et al. 2017), and high-income groups (Curtale et al., 2021a; 2021b). Owning several cars is associated with lower intention to use CS and ECS (Burghard and Dütschke 2019; Ohta et al. 2013). For AVs, fewer studies have examined the association between socio-demographics and behavioral intention. Age presents a negative, albeit weak, association with intention to use (Haboucha et al. 2017; Kaye et al. 2020; Kettles & van Bell 2019). Some studies have shown that males may be less concerned about the safety of AVs and have a higher intention to use them (Abay and Mannering 2016; Liljamo et al. 2018; Wadud & Chintakayala 2021). Education level has not always been a clear indicator in one direction, although the highly-educated tend to be less concerned about the safety of AVs (Barbour et al., 2019; Haboucha et al. 2017). Car ownership and high income, despite being found to have insignificant impacts in an analysis using TPB (Yuen et al. 2020), are often considered relevant to the acceptance of AVs in the literature (Panagiotopoulos & Dimitrakopoulos 2018; Wadud & Chintakayala 2021). There is little research devoted to the relationship between the size of a city and the intention to use AVs, although much research on the effects of this technology has been done in urban areas (Duarte and Ratti 2018) and seems to indicate that living in urban areas is positively associated with their acceptance (Liljamo et al. 2018). We hypothesize that in bigger cities, the behavioral intention may be higher due to a higher chance of becoming familiar with AVs. Empirically, car ownership is a positive factor of intention to use AVs (Lee et al. 2019; Wadud & Chintakayala 2021). Since there is no research on the user acceptance

Table 2
Sub-hypotheses of hypothesis 1.

	ECS		AECS
H1a	PE → BI (+)	H1e	HM → BI (+)
H1b	EE → BI (+)	H1f	SC → BI (−)
H1c	SI → BI (+)		
H1d	HM → BI (+)		

(PE: performance expectancy, EE: effort expectancy, SI: social influence, HM: hedonic motivation, SC: safety concern, BI: behavioral intention, →: direction of impact, +/−: positive or negative impact)

of AECS, the sub-hypotheses related to AECS are based on the previous evidence of AVs. The second hypothesis is formulated as follows.

Hypothesis 2. *Socio-demographic variables have significant impacts on behavioral intention to use ECS and AECS* (Table 3).

Considering that AECS can be seen as a particular type of ECS, we hypothesize that behavioral intention to use regular ECS and AECS are positively correlated, indicating that a higher intention to use a regular ECS signifies a positive intention to use AECS. Thus, the third hypothesis is the following.

Hypothesis 3. *Behavioral intention to use ECS positively affects intention to use AECS.*

There is evidence that intention to use CS and ECS present differences in cultural or contextual effects (Curtale et al., 2021a; 2021b; Fleury et al. 2017; Tran et al. 2019). For example, in two empirical studies conducted in China (Tran et al. 2019) and the Netherlands (Curtale et al., 2021a; 2021b), social influence and effort expectancy play inconsistent roles. In our case, we compare four European countries that share a higher degree of cultural similarities but have different geographic and demographic configurations. The differences are associated with varied spatial and travel characteristics. To cite some, Italy is highly dependent on private cars, with 655 passenger cars every 1,000 inhabitants, significantly higher than 570 in France, 533 in Spain, and 517 in the Netherlands (EAMA 2021; Eurostat 2019; Rotaris 2021). In the Netherlands, there is a higher usage of bicycles and a stronger satisfaction for public transport owing to the well-developed infrastructure (Copenhagenize 2019). In Spain, one of the countries that might suffer most from anthropogenic climate change, buses are used more frequently than the European average (European Commission 2019).

Regarding the effects of socio-demographic characteristics, there are indications for different preferences towards CS. For instance, females are found to have a higher behavioral intention to use CS in Italy, in contrast to other countries (Rotaris 2021). In the Netherlands, there is no evidence of gender and income effects on the adoption of CS (Münzel et al. 2019), while they seem to be relevant factors to predict the behavioral intention of ECS (Curtale et al., 2021a; 2021b). It should be noted that these results are not based on the same research design and methodology. The lack of solid prior knowledge does not allow us to propose a specific hypothesis in specific countries. Consequently, the nature of this analysis is more exploratory rather than confirmatory. We hypothesize that the impacts of psychological factors and socio-demographic characteristics are different across the four countries, without particular expectations on the strength and direction of impacts. Thus, the fourth hypothesis is as follows.

Hypothesis 4. *The impacts of psychological factors and socio-demographic variables on behavioral intention to use ECS and AECS are heterogeneous across the four countries.*

In summary, the above conceptual model identifies the impacts of specific factors affecting the behavioral intention to use AECS in addition to the standard ones that have been demonstrated to affect the intention to use ECS in different spatial contexts. The conceptualization enriches the UTAUT2 by suggesting extra moderating (car ownership and city size), exogenous (safe concern), and endogenous variables (behavioral intention to use ECS) in the domain of AECS. Particularly, different from other extensions that are limited to one single technology or service (see an extensive review by Tamilmani et al. 2021), we propose the inclusion of transitional behavioral intention to use two adjacent generations of services that may co-exist for a long period. The alignment offsets in part the side effects of ruling out less relevant constructs to reduce the conceivable state space as a quest of the “principle of parsimony” (Weber 2012). Thus, this study offers a theoretical extension over the multi-level framework of Venkatesh et al. (2016) by investigating the transitional acceptance of upgraded technologies or services. Based on one common research design, the empirical results of the multigroup analysis can shed light on the development of dedicated deployment and management strategies.

Table 3
Sub-hypotheses of hypothesis 2.

ECS		AECS	
H2a	Gender: female → BI (−)	H2g	Gender: female → BI (−)
H2b	Age → BI (−)	H2h	Age → BI (−)
H2c	High education → BI (+)	H2i	High education → BI (+)
H2d	High income → BI (+)	H2j	High income → BI (+)
H2e	City size → BI (+)	H2k	City size → BI (+)
H2f	Car ownership → BI (−)	H2l	Car ownership → BI (+)

3. Survey, sample, and method

We present the survey instrument used to collect the data in Subsection 3.1, the sample characteristics in Subsection 3.2, and the analytical method to investigate the proposed hypotheses in Subsection 3.3.

3.1. Survey

One common online survey was deployed in the four countries, with translations into the respective languages provided by native language speakers within the research unit. The English version of the questionnaire used in the survey is available in the supplementary document. The questionnaire took around 8 min to be completed and is composed of three parts. The first part refers to socio-demographic characteristics, collected through multiple-choice questions. The second part includes questions regarding psychological constructs affecting behavioral intention to use ECS. It was specified that for using ECS, respondents can monitor the location of the cars and the charging stations through a smartphone-based application. The five psychological constructs are measured through a five-point Likert scale value assigned to sixteen measurement items, as displayed in Table 4.1. Respondents stated their levels of agreement on a scale ranging from 1 = "totally disagree" to 5 = "totally agree" with the middle point representing "neutral". The statements are adapted from the previous studies applying or extending the UTAUT and UTAUT2 (Fleury et al. 2017; Madigan et al. 2017; Tran et al. 2019; Venkatesh et al. 2003, 2012).

Soon after indicating judgments on ECS-related statements, respondents were invited to state their level of agreement regarding AECS in the third part. It is stressed in the survey that the standard electric vehicles in ECS are replaced by Level-5 fully autonomous electric vehicles, adopting vehicle-to-vehicle communication technology (V2V). We highlighted that while using AECS, respondents can perform other tasks other than driving, such as leisure activities, sleeping, or working. This part is composed of three constructs and ten measurement items, as displayed in Table 4.2. The statements of the hedonic motivation dimension are adapted from studies of Madigan et al. (2017), Tran et al. (2019), and Venkatesh et al. (2012), while those related to safety concern are based on the results of Kapser and Abdelrahman (2020) and Ribeiro et al. (2021).

The survey was administered simultaneously in France, Italy, Netherlands, and Spain between November 27 and December 18, 2020. A preliminary pre-test and a soft launch of 50 respondents per country had been conducted before the full launch to ensure the reliability of the questionnaire. During the period of data collection, these countries were experiencing the second or third wave of the COVID-19 pandemic. To control for possible biases due to the pandemical context, we included in the survey a latent variable capturing respondents' concerns regarding the effects of COVID-19. The latent variable is dropped out from the final analysis after preliminary tests of insignificance to ensure that the results are not biased due to COVID-19.

3.2. Sample description

Before participating in the survey, every respondent received detailed explanations of the mobility services (e.g., characteristics of the vehicles and transaction information systems) and instructions for completing the survey. The target population was adults with driving licenses. To ensure representative subsamples, respondents were recruited from two large panels for market research. Data of

Table 4.1
Constructs and statements for ECS.

Constructs		Main sources
Performance expectancy (PE)		
PE1	I expect that ECS will help me save travel time.	Fleury et al. 2017; Tran et al. 2019; Venkatesh et al. 2003, 2012
PE2	I expect that ECS will help me transfer to other transport modes.	
PE3	I expect that ECS will enhance my engagement in activities at the destinations.	
Effort expectancy (EE)		
EE1	I expect it easy to learn how to use the e-car.	Fleury et al. 2017; Tran et al. 2019; Venkatesh et al. 2003, 2012
EE2	I expect it easy to become skillful at using the ECS.	
EE3	I expect a clear and understandable interaction with the ECS.	
Social influence (SI)		
SI1	People who are important to me think that I should use the ECS.	Fleury et al. 2017; Tran et al. 2019; Venkatesh et al. 2003, 2012
SI2	People whose opinions I value think that I should use the ECS.	
SI3	It seems that my friends/colleagues are using ECS.	
Hedonic motivation (HM)		
HM1	I think using ECS is fun.	Tran et al. 2019; Venkatesh et al. 2012
HM2	I think using ECS is entertaining.	
HM3	I think using ESC is enjoyable.	
Behavioral intention (BI)		
BI1	I intend to use the ECS occasionally.	Fleury et al. 2017; Tran et al. 2019; Venkatesh et al. 2003, 2012
BI2	I intend to use the ECS when there are promotions.	
BI3	I intend to use the ECS for my regular trips.	
BI4	I would encourage my friends/colleagues to use the ECS.	

Table 4.2
Additional constructs and statements for AECS.

Constructs		Main sources
Hedonic motivation AECS (HM-A)		
HM-A1	I think using AECS is fun.	Madigan et al. 2017; Tran et al. 2019; Venkatesh et al. 2012
HM-A2	I think using AECS is entertaining.	
HM-A3	I think using AECS is enjoyable.	
Safety concern AECS (SC-A)		
SC-A1	I think AECS is not ready for public use in urban mobility.	Kapser and Abdelrahman 2020; Ribeiro et al. 2021
SC-A2	I think AECS is a threat to other vehicles and pedestrians.	
SC-A3	I think AECS is not secure enough for travelers.	
Behavioral intention (BI-A)		
BI-A1	I intend to use the AECS occasionally.	Fleury et al. 2017; Madigan et al. 2017; Tran et al. 2019; Venkatesh et al. 2003, 2012
BI-A2	I intend to use the AECS when there are promotions.	
BI-A3	I intend to use the AECS for my regular trips.	
BI-A4	I would encourage my friends/colleagues to use the AECS.	

the Dutch sample were collected by Panelclix[1], and data of the French, Italian, and Spanish samples by Dynata[2]. Respondents presenting no variation at all in the Likert scale questions (e.g. those responding systematically "3″ or "5" to all questions) have been excluded from data analysis. The final aggregated sample is composed of 2,154 respondents, 621 from the Netherlands, 546 from Italy, 495 from Spain, and 492 from France. The sample composition is shown in Table 5.

The samples are representative of age structure and balanced in terms of gender, except for a slight over-representation of males in the Spanish sample. Highly-educated people are more represented than those in the real population due to the high internet penetration of this group, as often shown in studies using market research agencies. The Italian sample has the lowest percentage of respondents with higher education, but the level is comparable with those of other countries. Higher incomes are present in the Dutch and French samples compared to the Italian and Spanish ones, reflecting the actual population distributions. The French sample has the highest ratio of respondents living in smaller cities (with less than 20 k inhabitants), while the Spanish one has the highest percentage of respondents living in big cities (with more than 500 k inhabitants). As expected, the respondents or their households have a high level of car ownership. Overall, except for an over-representation of highly-educated people, the samples are in line with the statistics of the four countries.

3.3. Method

Psychological factors are measured and validated through confirmatory factor analysis (CFA) (Brown 2015). The internal consistency of the factors is measured through the Cronbach's alpha indicator (Santos 1999). The relationships between psychological factors, socio-demographic characteristics, and the behavioral intention to use ECS and AECS are investigated through structural equation modeling (SEM) applied to the latent variables measured through the 5-point Likert scale items (Ullman and Bentler 2003). Multigroup analysis of constrained models is performed to assess impact differences across countries. Analyses are conducted through the lavaan package (Rosseel 2012) of the R software.

We first test hypotheses H1-H3 in a general model. Then, we test if the impacts of regressors on behavioral intention to use ECS and AECS are heterogeneous across countries (H4) through the multigroup analysis. To test H4, in the first step, we estimate an unconstrained model, in which the parameters capturing the impacts of psychological factors are freely estimated in all countries. In the second step, we impose constraints of equality to some parameters that do not present statistical differences across countries. In this way, we can identify which factors are country-specific and which factors are important drivers of behavioral intention regardless of the context.

4. Results

This section first presents the descriptive statistics of the measurement items and the results of the CFA in Subsection 4.1. The SEM results are reported in Subsection 4.2, with a part addressing the moderating effects on the UTAUT2 dimensions and another part showing the impacts of the UTAUT2 dimensions. The results of the multigroup analysis are discussed in Subsection 4.3.

4.1. Item statistics, reliability, and CFA results

The statements used to measure psychological constructs, also known as measurement items, receive scores from one to five. The descriptive statistics regarding the mean, standard deviation, and skewness of the items as well as the construct averages are shown in Table 6.

[1] https://www.panelclix.co.uk.
[2] https://www.dynata.com.

Table 5
Sample composition.

Variables	Netherlands	Italy	Spain	France
number of respondents	621	546	495	492
Gender				
male	313 (50%)	266 (49%)	261 (53%)	239 (49%)
female	308 (50%)	280 (51%)	234 (47%)	253 (51%)
Age				
<20 years old	37 (6%)	34 (6%)	27 (5%)	42 (9%)
21–30 years old	102 (16%)	74 (14%)	76 (15%)	68 (14%)
31–40 years old	107 (17%)	106 (19%)	123 (25%)	94 (19%)
41–50 years old	102 (16%)	119 (22%)	112 (23%)	100 (20%)
51–60 years old	120 (19%)	90 (16%)	86 (17%)	54 (11%)
61–70 years old	104 (17%)	93 (17%)	55 (11%)	105 (21%)
more than 70 years old	49 (8%)	30 (5%)	16 (3%)	29 (6%)
Education				
low (high school diploma or lower)	313 (50%)	332 (61%)	222 (45%)	236 (48%)
high (bachelor degree or higher)	308 (50%)	214 (39%)	273 (55%)	256 (52%)
Income				
low (below 2 k €/month net)	365 (59%)	413 (76%)	377 (76%)	282 (57%)
high (higher than 2 k €/month net)	256 (41%)	133 (24%)	118 (24%)	210 (43%)
City size				
small (<20 k)	169 (27%)	147 (27%)	91 (18%)	235 (48%)
medium (between 20 k and 500 k)	393 (63%)	294 (54%)	270 (55%)	209 (42%)
large (more than 500 k)	59 (10%)	105 (19%)	134 (27%)	48 (10%)
Car ownership in the household				
no	84 (14%)	52 (10%)	50 (10%)	70 (14%)
yes	537 (86%)	494 (90%)	445 (90%)	422 (86%)

The means of the majority items have a score higher than three, which represents the median level, except for social influence and behavioral intention to use AECS. Hedonic motivation is similar for ECS and AECS, while behavioral intention for ECS is slightly higher than that for AECS. All standard deviations are around one, indicating heterogeneous responses for every item. Skewness is mostly negative, indicating asymmetric left-skewed distributions. In general, all the items have enough variations to perform factor analysis. With the proposed items, CFA is conducted to estimate the psychological factors and test if the data fit the proposed model. As shown in Table 7, the Cronbach's alphas are above 0.81 for all the constructs and the average variances extracted are above 0.82, indicating the reliability and validity of the constructs. The CFA outputs acceptable goodness-of-fit (Cronbach's alpha > 0.8, AVE > 0.8, CFI $= 0.950$, RMSEA $= 0.061$, SRMR $= 0.029$), indicating that the measurement model is validated by the data.

4.2. SEM results

We first show the impacts of socio-demographic characteristics on UTAUT2 dimensions. In what follows, the impacts of UTAUT2

Table 6
Item statistics ($N = 2{,}154$ respondents).

Constructs	Item	Mean ECS	St. Dev.	Skew.	Constr. Avg.	Mean AECS	St. Dev.	Skew.	Constr. Avg.
Performance expectancy	PE1	3.19	1.07	−0.37	3.24				
	PE2	3.34	1.08	−0.47					
	PE3	3.18	1.08	−0.30					
Effort expectancy	EE1	3.91	0.89	−0.88	3.89				
	EE2	3.89	0.90	−0.85					
	EE3	3.85	0.90	−0.79					
Social influence	SI1	2.92	1.14	−0.10	2.84				
	SI2	2.93	1.12	−0.17					
	SI3	2.66	1.16	0.05					
Hedonic motivation	HM1	3.34	1.01	−0.44	3.37	3.35	1.00	−0.48	3.36
	HM2	3.30	1.01	−0.38		3.32	0.99	−0.45	
	HM3	3.47	0.98	−0.55		3.42	0.98	−0.55	
Safety concern	SC1					3.30	1.06	−0.30	3.15
	SC2					3.02	1.08	−0.07	
	SC3					3.13	1.03	−0.17	
Behavioral intention	BI1	3.06	1.14	−0.28	3.06	2.99	1.13	−0.28	2.95
	BI2	3.14	1.14	−0.34		3.04	1.16	−0.30	
	BI3	2.93	1.16	−0.13		2.81	1.18	−0.06	
	BI4	3.13	1.11	−0.33		2.96	1.13	−0.19	

(St. Dev.: standard deviation, Skew.: skewness, Constr. Avg.: average of the construct)

Table 7
Cronbach's alpha, average variance extracted (AVE), and CFA model fit.

Constructs	Cronbach's alpha	AVE
ECS		
Performance expectancy	0.88	0.89
Effort expectancy	0.84	0.85
Social influence	0.89	0.90
Hedonic motivation	0.89	0.89
Behavioral intention	0.91	0.90
AECS		
Hedonic motivation	0.89	0.91
Safety concern	0.81	0.82
Behavioral intention	0.92	0.93
CFA model fit	**Values**	
Comparative Fit Index (CFI)	0.950	
Root Mean Square Error of Approximation (RMSEA)	0.061	
Standardized Root Mean Square Residual (SRMSR)	0.029	

dimensions and socio-demographic characteristics on behavioral intentions are discussed. For socio-demographic characteristics, both the direct effects on behavioral intention and the indirect effects, mediated by other psychological factors, are reported.

4.2.1. *Impacts of socio-demographic characteristics on UTAUT2 dimensions*

Regression results of socio-demographic characteristics on UTAUT2 dimensions are shown in Table 8, in which dependent variables are shown in the first row and regressors are shown in the first column. The results show that the UTAUT2 dimensions are heterogeneous depending on the socio-demographic characteristics of the respondents. Note that age level is coded continuous in the analysis and all the other variables are dummy-coded with the comparison level displayed in parenthesis.

For the ECS, performance expectancy significantly decreases with increasing age and income level, and it is higher as the size of the city increases and for car owners. Effort expectancy depends on education level and car ownership. Respondents with higher education and car ownership expect a lower required effort when learning how to use ECS. Social influence is lower for females, decreases with age, increases with income, and is higher in bigger cities and for car owners. Hedonic motivation presents similar patterns for both ECS and AECS; it decreases with age and is higher in bigger cities and for car owners. Safety concern of AECS is higher for females and lower in smaller cities. Unexpectedly, education level does not affect safety concern, and there is no gender effect in hedonic motivation.

4.2.2. *Behavioral intention towards ECS and AECS*

The impacts of psychological factors on the intention to use ECS and AECS are shown in Table 9. For the psychological factors, the total effects are equal to the direct effects. For socio-demographic characteristics, the total effects are the sum of the direct effects and the effects mediated by the other psychological factors (see Table 8). The variability of behavioral intention to use ECS is explained for 64% by the proposed psychological factors and socio-demographic characteristics. All the UTAUT2 dimensions have positive impacts on behavioral intention to use ECS. Therefore, hypotheses H1a to H1d are confirmed. Amongst, social influence has the strongest impacts, followed by performance expectancy and hedonic motivation. Regarding socio-demographic characteristics, age has a negative effect on behavioral intention, indicating that younger generations are more willing to use ECS. Education level has a positive direct effect, but the mediation of other psychological factors makes its total effects non-significant. Gender and income have neither direct nor total significant impact. City size and car ownership have no direct impact on behavioral intention, but they have significant total impacts due to mediation. It is noteworthy that the size of the city matters and respondents in smaller cities are less willing to use the ECS compared to those in bigger cities.

The variability of behavioral intention to use AECS is explained for 72% by the proposed psychological factors and socio-

Table 8
Regression results of UTAUT2 dimensions.

Variables	ECS				AECS	
	Performance expectancy	Effort expectancy	Social influence	Hedonic motivation	Hedonic motivation	Safety concern
Gender (female)	0.01	<0.01	−0.11**	−0.05	−0.03	0.06*
Age	−0.10***	−0.01	−0.14***	−0.10***	−0.11***	0.01
Education (high)	−0.02	0.09***	−0.05	−0.02	−0.03	0.03
Income (high)	−0.09**	−0.03	0.09*	0.01	0.03	0.02
City size (<20 k)	−0.13***	−0.02	−0.14***	−0.12***	−0.11**	−0.06*
City size (more than 500 k)	0.29***	0.07	0.29***	0.23***	0.14**	0.03
Car ownership (yes)	0.24***	0.16***	0.29***	0.24***	0.13**	0.04

(***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.1).

Table 9
Regression results of behavioral intention to use ECS and AECS (direct and total effect).

Variables	ECS		AECS	
	Direct effect	Total effect (direct + mediated)	Direct effect	Total effect (direct + mediated)
Performance expectancy	0.37***	0.37***		
Effort expectancy	0.06***	0.06***		
Social influence	0.38***	0.38***		
Hedonic motivation	0.29***	0.29***	0.30***	0.30***
Safety concern			−0.09***	−0.09***
Behavioral intention ECS			0.74***	0.74***
Gender (female)	<0.01	−0.05	−0.03	−0.05**
Age	−0.02*	−0.13***	−0.01	−0.04***
Education (high)	0.05*	0.02	−0.01	−0.02
Income (high)	0.02	0.02	0.07***	0.08***
City (<20 k)	−0.05	−0.18***	−0.01	−0.03
City (more than 500 k)	−0.01	0.28***	−0.03	0.01
Car ownership (yes)	<0.01	0.28***	0.03	0.07
R-squared	0.64		0.72	

(***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.1)

demographic characteristics. This value manifests a high explanatory power of the model provided with one fewer construct compared with those of ECS. The behavioral intention to use ECS stands out as a strong and significant predictor of intention to use AECS, confirming H3. The other two psychological factors are also relevant for the use of AECS, with hedonic motivation being a positive driver, while safety concern results in a significant deterrent. Therefore, hypotheses H1e and H1f are supported. Interestingly, the magnitude of the impact of hedonic motivation is much higher than that of safety concern, meaning that positive emotions have a stronger role than negative concern. Regarding the role of socio-demographic characteristics, the profile of respondents willing to use AECS corresponds to males, younger generations, and the higher income groups. A diagrammatic representation of the main results is displayed in Fig. 3.

All in all, the strong positive impact of behavioral intention to use ECS on the intention to use AECS indicates that ECS users are typically willing to adopt ECS when equipped with AVs. According to the transmission rule, the impacts of performance expectancy, effort expectancy, and social influence for ECS can be considered, to a large extent, relevant for the intention to use AECS.

4.3. Multigroup analysis

To investigate inter-country differences, a multigroup analysis is conducted on the SEM presented above. Table 10 shows the model fit comparisons of one unconstrained and two constrained models.

In the fully constrained model (1), the coefficients representing the impacts on behavioral intentions are the same across countries. In the unconstrained model (2), the impacts of all regressors on behavioral intention are estimated country-specific. In the partially

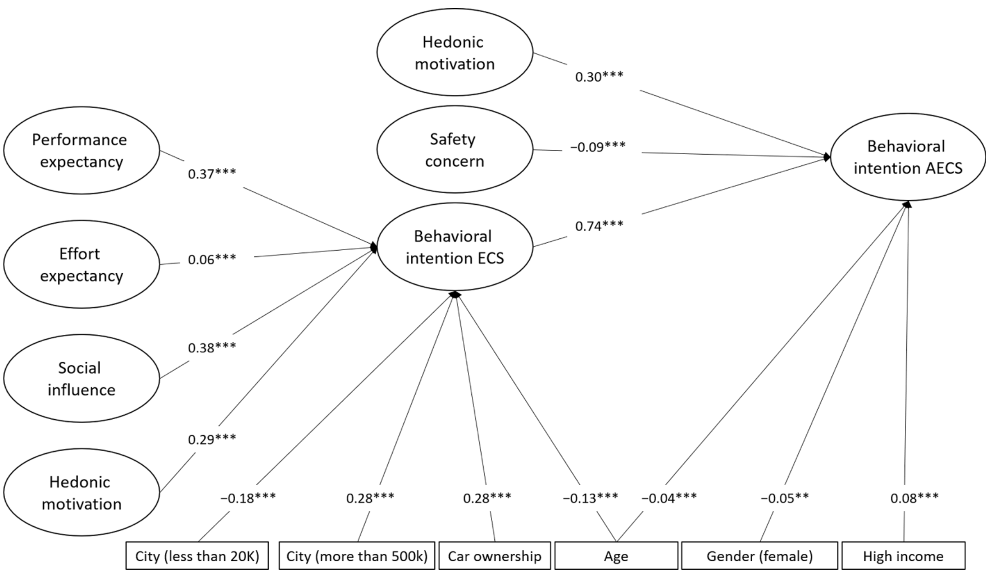

Fig. 3. Diagram of the total impacts of UTAUT2 dimensions and socio-demographic variables on behavioral intention to use AECS (***: p-value < 0.01, **: p-value < 0.05).

Table 10
Comparison of model fits of constrained and unconstrained models.

Model	CFI	TLI	AIC	BIC	RMSEA	SRMR	DF	Chi-Sq	Diff.
Fully constrained model (1)	0.910	0.903	121,933	**123,987**	0.061	0.077	**1874**	5627.8	
Unconstrained model (2)	0.914	0.902	121,867	124,455	0.061	**0.075**	1780	5374.1	<1e-3***
Partially constrained model (3)	**0.914**	**0.904**	**121,824**	124,117	**0.060**	0.076	1832	5435.1	0.18

(CFI: Comparative Fit Index; TLI: Tucker-Lewis Index; AIC: Akaike Information Criteria; BIC: Bayesian Information Criteria; RMSEA: Root Mean Square Error of approximation; SRMR: Standardized Root Mean Square Residuals; DF: degree of freedom; Chi-Sq: chi-square statistic; Diff.: p-value of the comparison with the previous model)

constrained model (3), some coefficients are constrained to be equal across countries, while some are unconstrained or country-specific. Model (2) is significantly better than model (1) in terms of overall model fits, indicating the presence of heterogeneous impacts. Starting from model (2), an iterative process is applied to reduce the number of coefficients by imposing equality to those that do not present differences across countries. Model (3) is not significantly different from model (2) but has better AIC and BIC values. In other words, model (3) fits the data as well as the unconstrained model, but it is more parsimonious in terms of parameters. For these reasons, model (3) is selected as the final model for multigroup comparisons. The direct effects of psychological factors and socio-demographic characteristics on behavioral intention are shown in Table 11 for the four countries. The variables that are constrained have exactly the same impacts on behavioral intention in different countries, while those presenting country-specific effects are attached with superscript ‘s’.

Results of the final constrained model show that the impacts of psychological factors and socio-demographic characteristics differ across countries, confirming H4. In particular, for behavioral intention to use ECS, the impact of performance expectancy is the highest for the Dutch respondents and the lowest for the Italian respondents; effort expectancy is not significant when considered in specific countries with smaller sample sizes. Social influence has a stronger impact in the French sample compared to the other countries, while hedonic motivation is higher in Italy and the Netherlands. Regarding the role of socio-demographic characteristics, behavioral intention is higher for younger generations and lower for those living in smaller cities.

The behavioral intention to use AECS also presents differences across countries. The behavioral intention to use ECS is a stronger predictor of intention to use AECS in Spain. The impact of hedonic motivation is the highest in Italy, followed by the Netherlands and then the other two countries. Safety concern seems to be a stronger deterrent of behavioral intention in the Netherlands. It has a lower impact in Italy and Spain and is not even significant in France. Respondents with higher incomes have higher behavioral intention, while females and those living in smaller cities present lower behavioral intention to use AECS in the Dutch and French samples.

The tests of all the hypotheses are summarized in Table 12. Note that hypotheses H1 to H3 are presented in rows and the inter-country differences supporting H4 are shown in the last column for a compact visualization. The column “Supported (mediating variable)” shows the test results of H1-H3. The columns “NL”, “IT”, “ES”, and “FR” indicate if the hypotheses are supported in the corresponding countries. Column “H4” shows whether there is a significant difference in the impact of every specific variable across countries. As seen, H1 is supported by the analysis. The endorsement of H2 is limited to age for behavioral intention to use both ECS

Table 11
Multigroup analysis of behavioral intention to use ECS and AECS – model (3).

Variables	Netherlands	Italy	Spain	France
Dependent variable: behavioral intention ECS				
Performance expectancy	0.48***^{s}	0.14***^{s}	0.34***	0.34***
Effort expectancy	0.04	0.04	0.04	0.04
Social influence	0.32***	0.32***	0.32***	0.39***^{s}
Hedonic motivation	0.34***	0.34***	0.21***	0.21***
Gender (female)	0.01	0.01	0.01	0.01
Age	−0.03**	−0.03***	−0.03***	−0.03***
Education (high)	0.04	0.04	0.04	0.04
Income (high)	0.04	0.04	0.04	0.04
Town (<20 k)	−0.06**	−0.06**	−0.06**	−0.06**
City (more than 500 k)	−0.01	−0.01	−0.01	−0.01
Car ownership (yes)	0.03	0.03	0.03	0.03
Dependent variable: behavioral intention AECS				
Hedonic motivation	0.30***^{s}	0.35***^{s}	0.25***	0.25***
Safety concern	−0.17***^{s}	−0.08***	−0.08***	−0.02 ^{s}
Behavioral intention ECS	0.71***	0.71***	0.77***^{s}	0.71***
Gender (female)	−0.08**	−0.01	−0.01	−0.08**
Age	−0.01	−0.01	−0.01	−0.01
Education (high)	−0.01	−0.01	−0.01	−0.01
Income (high)	0.07**	0.07**	0.07**	0.07**
Town (<20 k)	−0.06*	0.05	0.05	−0.06*
City (more than 500 k)	−0.02	−0.02	−0.02	−0.02
Car ownership (yes)	0.04	0.04	0.04	0.04

(***: p-value < 0.01, **: p-value < 0.05, *: p-value < 0.1, ^{s}: country-specific effect)

Table 12
Summary of hypothesis testing.

Hypothesis	Supposed path and impact	Supported (mediating variable)	NL	IT	ES	FR	*H4*
H1a	PE → BI (+)	yes	yes	yes	yes	yes	yes
H1b	EE → BI (+)	yes	–	–	–	–	–
H1c	SI → BI (+)	yes	yes	yes	yes	yes	yes
H1d	HM → BI (+)	yes	yes	yes	yes	yes	yes
H1d	HM → BI-A (+)	yes	yes	yes	yes	yes	yes
H1e	SC → BI-A (−)	yes	yes	yes	yes	–	yes
H2a	Gender (female) → BI (−)	–	–	–	–	–	–
H2b	Age → BI (−)	yes	yes	yes	yes	yes	–
H2c	Education (high) → BI (+)	yes	–	–	–	–	–
H2d	Income (high) → BI (+)	–	–	–	–	–	–
H2e	City size → BI (+)	yes	yes	yes	yes	yes	–
H2f	Car ownership → BI (−)	–	–	–	–	–	–
H2g	Gender (female) → BI-A (−)	yes (SC)	yes	–	–	yes	yes
H2h	Age → BI-A (−)	yes (HM)	–	–	–	–	–
H2i	Education (high) → BI-A (+)	–	–	–	–	–	–
H2j	Income (high) → BI-A (+)	yes	yes	yes	yes	yes	–
H2k	City size → BI-A (+)	–	yes	–	–	yes	yes
H2l	Car ownership → BI-A (+)	–	–	–	–	–	–
H3	BI → BI-A (+)	yes	yes	yes	yes	yes	yes

(NL: Netherlands, IT: Italy, FR: France, ES: Spain; BI and BI-A: behavioral intention to use ECS and AECS, respectively; for other abbreviations, refer to Tables 4.1 and 4.2)

and AECS, for education and city size to use ECS and for gender and income to use AECS. H3 is supported due to the positive impacts of behavioral intention to use ECS. H4 is supported as the impacts of most psychological factors and socio-demographic characteristics are heterogeneous across countries. Note that some variables have significant effects in the aggregated sample, but they are not significant in country-specific analyses (e.g., effort expectancy and high education). The inconsistency is due to the higher statistical power of a large sample. It can be seen that such variables usually have lower impacts on behavioral intention in the larger sample and the significance is not evident in smaller samples.

5. Discussion

The above analysis offers multi-faceted insights into the behavioral intention to use ECS and AECS. This section discusses the results and their relevance to the literature. Managerial implications are then provided to service operators and public institutions for dedicated deployment and management of such services.

5.1. Relevance to the literature

As far as the transition is concerned, the behavioral intention to use ECS has a strong positive impact on the intention to use AECS. Therefore, it is important to have a preliminary overview of the characteristics of respondents interested in ECS before looking at those specific to AECS. Generally speaking, the intention to use ECS is significantly higher for younger generations and those living in bigger cities. The results confirm the evidence of other studies that identified a decreasing intention to use information system-based sharing mobility services for elderly people (Cartenì et al. 2016; Curtale et al., 2021a; 2021b; Efthymiou et al. 2013) and in smaller cities (Prieto et al. 2017). Our result is somehow expected given that in smaller cities, there might be less need for ECS as shorter travel distances for accessing facilities could be well entertained by active modes, local buses, or private cars without being afflicted by congestion and parking issues.

In contrast to other studies that find a higher behavioral intention to use ECS for males (Becker et al. 2017; Cartenì et al. 2016; Prieto et al. 2017; Curtale et al., 2021a; 2021b), we do not find a common gender effect in our analysis. Education level does not have a significant effect either in specific countries, while other studies found that higher education is associated with higher behavioral intention (Becker et al. 2017; Prieto et al. 2017). The impact of car ownership on the use of ECS is mediated by psychological factors in the opposite direction compared with other studies (Burghard and Dütschke 2019; Ohta et al. 2013). The difference might be explained by the fact that those studies considered the impact of the number of cars on behavioral intention, while we used one dummy variable for car ownership (yes or no). Similar to the case of ECS, young people, high-income earners, and city dwellers expect AECS to be enjoyable, and thus are associated with stronger intention. While there is no gender effect in hedonic motivation, females are more likely to be concerned about the safety aspects of AECS, which reduces their intention to use. As for the behavioral intention to use AECS, our results show that males, younger generations, and high income tend to be associated with a higher interest. The results confirm evidence from other studies that show how younger people are generally more interested in innovative transport modes such as AVs (Haboucha et al. 2017; Kaye et al. 2020; Kettles & van Bell 2019). Males present a higher intention to use AECS, and a particular reason could be the lower concern about safety issues, as shown in other studies (Abay and Mannering 2016; Liljamo et al. 2018; Wadud & Chintakayala 2021). Although there is no clear indication of the reasons behind the gender gap in safety concern, building confidence in females might increase their acceptance (Liljamo et al. 2018). High income is associated with higher intention to use

AECS, confirming the results from the literature indicating the high interest for AVs (Panagiotopoulos & Dimitrakopoulos 2018).

Regarding the psychological factors, the analysis results demonstrate that UTAUT2 dimensions affect the user acceptance of ECS and AECS. Performance expectancy is an important driver, which is consistent with the results of most studies in the transport field (Curtale et al., 2021a; 2021b; Kapser and Abdelrahman 2020; Leicht et al. 2018; Madigan et al. 2017; Ribeiro et al. 2021; Tran et al. 2019). As for effort expectancy, our results indicate that it has a low impact and its significance also depends on sample size. This result explains why it is a relevant factor only in some contexts (Fleury et al. 2017; Leicht et al. 2018; Tran et al. 2019), while other studies do not corroborate its significant impact (Curtale et al., 2021a; 2021b; Kapser and Abdelrahman 2020; Madigan et al. 2017). Social influence is a relevant construct in the four countries, confirming the result of studies conducted in other European countries (e.g., Kapser and Abdelrahman 2020; Madigan et al. 2017). The result implies that a large user community may be associated with high confidence in sharing mobility and positively impact the overall acceptance. Hedonic motivation is also a relevant driver of behavioral intention in the four countries. The results support the evidence of studies investigating the impact of ride enjoyment on behavioral intention to use other new transport services (Kapser and Abdelrahman 2020; Madigan et al. 2017; Ribeiro et al. 2021; Tran et al. 2019).

Some country-specific aspects emerged from the analysis. In the Netherlands, there is a higher impact of performance expectancy for ECS and safety concern for AECS, compared to other countries. Italy is characterized by a higher impact of hedonic motivation and a lower impact of performance expectancy for ECS. Spain has the highest transitional behavior from ECS to AECS, while in France, the role of social influence on ECS is the highest across the sample. Possible explanations can be formulated by looking at travel habits and other transport-related figures such as road fatality and car ownership. The Netherlands presents the highest share of bike usage (Fiorello et al. 2016) and the lowest ratio of road fatality per million inhabitants (European Commission 2020) of the four countries. With a relatively safer status quo compared to other countries, it is reasonable that safety concerns represent a deterrent for intention to use AECS. Italy has the highest car ownership (EAMA 2021) and car usage (Fiorello et al. 2016). The high penetration of cars across Italians could explain a lower need for ECS, and thus the lower impact of performance expectancy. Additionally, the higher value of hedonic motivation can be explained by the high diffusion of cars in Italy. This result indicates interest in the car industry, which could motivate the hedonic attractiveness for innovative technology such as AECS. In France, the greater impact of social influence on behavioral intention of ECS could be explained by the larger diffusion and higher confidence in sharing services compared to other countries (Prieto et al. 2017). The highest transitional behavior from ECS to AECS requires further investigation to provide a valid explanation.

5.2. Theoretical implications

From a theoretical point of view, our results show that behavioral intention to use AECS can be explained by the behavioral intention to use ECS, hedonic motivation, and safety concern. It indicates that ECS users are likely to be attracted by the possibility of using the service with autonomous vehicles. The intention to use AECS is positively influenced by the intention to use ECS, indicating that factors affecting the use of ECS are indirect drivers of AECS. The enjoyment of the ride, captured by hedonic motivation, is also relevant for AECS use in all the countries investigated, indicating that it is likely to be a triggering factor for AECS use regardless of the context. The intention to use AECS is mitigated by safety concern, which seems to be a mild deterrent for the behavioral intention given that its effect is lower and not proven to be significant in all countries. The theoretical output from our model seems promising for the development of AECS as it indicates that positive aspects (e.g. hedonic motivation) can have a stronger impact compared to negative ones (e.g. safety concern) for the intention to use. With this framework as background, strategical planning for the development of the AECS is possible by interpreting the country-specific impact of the relevant factors, which is provided in subsection 5.3.

5.3. Practical implications

The empirical results provide important insights for service operators and public institutions interested in offering AECS in urban areas. The deployment of AECS should take into consideration the fact that people's behavioral intentions are influenced by psychological factors, moderated by socio-demographic characteristics, and are heterogeneous across regions or countries. In line with the large evidence in the literature, good performance of the services is a necessary condition. In other words, if people do not expect a service to meet their mobility needs, they are very unlikely to use it. This aspect is particularly relevant in the Netherlands and Spain. Effort expectancy is the factor presenting the lowest impact on behavioral intention, indicating that the easiness to use such services is considered almost as a pre-requisite for the users. It is especially true for the transaction information system required to use the services (Degirmenci et al. 2017). Widespread adoption by the surrounding social network would increase their usage. Since the importance of social influence is the highest in France, marketing strategies based on referral promotions and social media advertising might be more effective in France compared to other countries. To spur wider adoption, service operators can leverage the enjoyable aspects of travel with AECS, which represent a relevant driver of intention to use across all countries. On the other side, the safety concern for AECS seems to be a mild deterrent for the behavioral intention.

From an operational and strategical perspective, it is interesting to note that, controlling for other factors, those who live in small cities are less likely to be concerned about safety. On the other hand, inhabitants of small cities are also less likely to be interested in using AECS due to hedonic motivation. This could suggest that while rural inhabitants do not see a hedonic motivation for the use of AECS, they are less worried about safety. Thus, government or municipalities interested in approving future AECS testing fields can consider rural settings as an advisable ground. This is salient because there has been much discussion regarding the use of AECS in rural environments that are currently underserved by public transport (Milakis et al. 2017). Across countries, a major difference in negative intention towards using AECS was seen in the respondents from the Netherlands, who were markedly less likely to use AECS due to safety concern. This result is surprising given that a large amount of AV testing and research has been and is currently being produced by Dutch institutions (Milakis et al. 2017). One potential reason for this could be that, while AECS are expected to be safe than human drivers, the Dutch take a prudent stance before a large proportion of the vehicle fleet is automated, given the current higher road safety compared to the other countries (European Commision 2020).

A summary of inter-country differences is shown in Table 13, in which we highlight the most impactful variable in every country. We list the top three psychological factors and the significant moderating socio-demographic characteristics for each country, based on the standardized impacts on behavioral intention to use ECS and AECS. Service operators can consult this table to design dedicated deployment strategies in areas of similar backgrounds.

As a side remark, it is important to notice that we refer to the behavioral intention to use AECS, but we cannot say with certainty how the future adoption will be. We show the relevant factors for the user acceptance of AECS in the form of a tendency other than the actual use. However, there is solid evidence that intentional or prior use plays a role in developing a positive attitude towards them, reinforcing future use behavior (Agudo-Peregrina et al. 2014). Thus, authorities interested in triggering the adoption of AECS might sponsor campaigns providing free trials of AECS as a strategy to build up travelers' intention and adoption. Given the positive transitional behavioral intention, AV producers may seize opportunities to familiarize ECS users with AVs to foster higher behavioral intention to use AECS or even buy AVs.

5.4. Limitations and future work

The results of this study present some limitations that set the stage for further research. First of all, it is important to note that we investigate behavioral intention, which is just one driver of actual use behavior. Although the knowledge of behavioral drivers is necessary before deploying technology at large scales, other factors such as market conditions, facilitating conditions, or habits can weaken the actual use. Second, our study considers a compact set of variables, which we considered as the most relevant, but future studies could include other factors, such as facilitating conditions, habits, and price value, and investigate the link between behavioral intention and actual use, especially after AECS gain popularity. Our study is the first attempt to explain transitional behavior with an extended UTAUT2, but other framework may be acceptable alternatives based on solid conceptualizations. Therefore, more verifications, validations, and comparisons with the original UTAUT2 framework in other contexts would be required for a stronger consolidation of the reliability of our results. Third, our model cannot provide usage forecasts. To obtain forecasts based on the constructs presented in this paper, in future studies the latent factors will be integrated into stated or revealed choice surveys to elicit travel preferences in hybrid choice models. It would be interesting to investigate how the psychological factors can affect the actual use of such services in the real world and how they can replace the use of private vehicles. Fourth, the replication of the same research framework in other regions contributes to drawing a complete picture of the roles that psychological factors have on behavioral intention to use AECS. Fifth, the results indicate that ECS users will, to a large extent, be interested in AECS, but the reverse is possible as well. For example, in a mixed environment of ECS and AECS, non-ECS users who are attracted by AVs may develop a higher interest in ECS after using AECS. The relationship will be better tested when the actual implementation of AVs in ECS takes place. Finally, additional research should consider the potential changes caused by AECS in social dynamics in the years to come. For example, it is of great interest to measure if the ability to travel further with less discomfort with AECS could lead to de-urbanization dynamics. We will address these issues in our future work.

6. Conclusions

AECS could be an important part of a future solution to tackle the negative urban mobility externalities. This study suggests a theoretical model based on the UTAUT2 to investigate the transitional behavioral intention to use AECS. The model encompasses the transitional user acceptance of ECS, which are currently flourishing in developed and emerging markets. The results of structural equation models applied to a large-scale survey collected in four European countries show that the behavioral intention to use AECS is heterogeneous and can be explained by psychological factors and socio-demographic characteristics. The current profile of users interested in AECS seems to be younger generations and wealthier people with higher levels of education. Nonetheless, the

Table 13
Inter-county comparisons of important drivers.

Type of CS	Netherlands	Italy	Spain	France
ECS	Psychological factors			
	1. PE (+)2. HM (+)3. SI (+)	1. HM (+)2. SI (+)3. PE (+)	1. PE (+)2. SI (+)3. HM (+)	1. SI (+)2. PE (+)3. HM (+)
	Socio-demographics			
	age (−)city size (+)	age (−)city size (+)	age (−)city size (+)	age (−)city size (+)
AECS	Psychological factors			
	1. BI-ECS (+)2. HM (+)3. SC (−)	1. BI-ECS (+)2. HM (+)3. SC (−)	1. BI-ECS (+)2. HM (+)3. SC (−)	1. BI-ECS (+)2. HM (+)
	Socio-demographics			
	income (+)city size (+)female (−)	income (+)city size (+)	income (+)city size (+)	income (+)city size (+)female (−)

(PE: performance expectancy, EE: effort expectancy, SI: social influence, HM: hedonic motivation, SC: safety concern, BI: behavioral intention, +/−: positive or negative impact) encouraging evidence is that behavioral intention is affected by psychological factors. Based on their standardized impacts on behavioral intention, we have elaborated on the managerial implications to widen the market base. Particularly, ECS operators are recommended to build a strong social community of users, who are likely to remain loyal when AVs are embedded in ECS. Thereafter, marketing campaigns that raise public perception of AECS being reliable with respect to performance, easy to use, and enjoyable should be prioritized to make AECS a mainstream in the passenger mobility sector.

CRediT authorship contribution statement

Riccardo Curtale: Conceptualization, Methodology, Investigation, Validation, Writing – original draft. **Feixiong Liao:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Ella Rebalski:** Investigation, Writing – original draft.

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. Supplementary material

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