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ABSTRACT

The study investigated the interrelationships between the UTAUT2 (Unified Theory of Acceptance and Use of Technology) constructs predicting intentions to use driverless automated shuttles. Survey data was gathered from individuals physically experiencing an automated shuttle in a mixed traffic environment on public roads in Trikala (Greece) as part of the CityMobil2 project. Structural equation modelling showed that intentions to use automated shuttles were most strongly driven by hedonic motivation, followed by performance expectancy and social influence. Performance expectancy mediated the relationship between effort expectancy and behavioural intention. This means that people's expectations of how difficult automated shuttles will be to use and their intentions to use them can be explained through their expectations around how these vehicles will perform. Technology savviness was a negative moderator of the relationship between social influence and performance expectancy and facilitating conditions, respectively. Tech-savvy individuals rely less on their social networks to nurture their beliefs that automated shuttles are useful and to have the necessary resources to use automated shuttles. Car use was a negative predictor of the intention to use automated shuttles. Future research should revisit the interrelationships between the UTAUT2 constructs and apply (quasi-) experimental studies to unravel the temporal interaction between constructs.

Relevance to human factors/Relevance to ergonomics theory

The study investigated the interrelationships between the UTAUT2 (Unified Theory of Acceptance and Use of Technology) constructs predicting intentions to use driverless automated shuttles. Survey data from individuals physically experiencing an automated shuttle in Trikala (Greece) as part of the CityMobil2 project was analysed by structural equation modeling. Examining the interrelationships between the UTAUT2 constructs enables us to identify underlying beliefs and devise adequate strategies to promote automated vehicle acceptance.

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1. Introduction

The debate on how to reduce car ownership and car use has been ongoing for at least four decades (Cullinane 2002). Governmental policies to encourage the use of public transport tend to yield marginal and temporary reductions in private car use, and often lead to car redistribution rather than reductions in car traffic, congestion and environmental pollution (Cullinane 2002; Younes 1995). Hensher (1998, 193) asserted that *"no public transport system within affordable political budgets is ever likely to provide a level of service of sufficient appeal to attract a large number of car users to switch to public transport"*. The advent of automated shuttles as feeders to public transport systems could instigate a paradigm shift towards more environmentally-friendly mobility by covering both the access and regress end of a public transport trip, thereby increasing the efficiency of public transport (Soteropoulos, Berger, and Ciari 2019). With driverless operation, smaller vehicles become relatively economic, creating scope for flexible on-demand 24/7 operation.

Automated shuttles as feeders to public transport systems are currently being tested in a number of public trials, mostly in low-speed, controlled, semi-public environments. The commercial deployment of automated Shuttles in more dynamic, mixed traffic situations on public roads is expected soon, probably by the end of this decade (Beiker 2019; Stocker and Shaheen 2019). These expectations, however, can only be realized if automated shuttles are accepted and used as intended.

A growing body of literature is examining automated vehicle acceptance. This study builds on the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Thong, and Xu 2012). UTAUT posits that performance expectancy (i.e., degree to which using a technology will provide benefits to consumers in performing certain activities), effort expectancy (i.e., degree of ease associated with consumers' use of technology), social influence (i.e., degree to which consumers perceive that important others believe they should use a particular technology), and facilitating conditions (i.e., consumer's perceptions of the resources and support available to perform a behaviour) influence the behavioural intention of an individual to use a technology, while behavioural intention and facilitating conditions determine actual system usage (Venkatesh et al. 2003). UTAUT2 suggests that an individual's behavioural intention to use information technology is influenced by three constructs in addition to the original UTAUT constructs, i.e., hedonic motivation (i.e., fun or pleasure derived from using a technology), price value (i.e., monetary cost of technology use), and habit (i.e., degree to which an individual believes the behaviour to be automatic) (Venkatesh, Thong, and Xu 2012, 161).

Madigan et al. (2017) showed that the UTAUT2 constructs performance expectancy, social influence, facilitating conditions, and hedonic motivation predict the behavioural intention to use automated shuttles. This paper aims to enhance our understanding of the process leading to behavioural intention investigating the interrelationships between the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation. The relevance of examining the relationships between technology acceptance constructs has been acknowledged (Karahanna, Agarwal, and Angst 2006). There is still limited knowledge about the interrelationships between the various factors impacting automated vehicle acceptance, including the UTAUT2 constructs. Acheampong and Cugurullo (2019) argue that automated vehicle acceptance is a complex and multifaceted research theme that can only be fully understood when an interdisciplinary perspective is adopted and the interrelationships between various acceptance factors are

considered. For example, the literature on automated vehicle acceptance has identified the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation as predictors of individuals' behavioural intentions to use automated shuttles. However, there is limited knowledge about the factors that determine the UTAUT2 predictors. Thus, beyond asking *„To what extent do performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation predict the behavioural intention to use automated shuttles?",* we direct our attention to research questions like: *„Which factors predict performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation?"* Examining the interrelationships between the UTAUT2 constructs thus enables us to identify underlying beliefs and devise adequate strategies to promote automated vehicle acceptance.

Madigan et al. (2017) did not consider the influence of car and public transport use, technology savviness and automated shuttle experience on the UTAUT2 predictor constructs and behavioural intention. Prior research has supported the role of these constructs for automated vehicle acceptance (Asgari and Jin 2019; Bansal, Kockelman, and Singh 2016; Lavieri et al. 2017; Shabanpour et al. 2017; Nordhoff, De Winter, et al. 2019). For these reasons, the present study examines the relationships between these factors and the UTAUT2 constructs.

1.1. Research objectives

The objectives of the current study, conducted as part of the CityMobil2 project, were therefore to examine:

1. Relationships between the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions and hedonic motivation
2. Relationships between a person's travel behaviour (i.e., measured by car and public transport use) and the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and individuals' behavioural intentions to use automated shuttles in public transport
3. Relationships between a person's travel behaviour (i.e., measured by car and public transport use) and the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and individuals' behavioural intentions to use automated shuttles in public transport
4. Relationships between a person's automated shuttle experience and the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and individuals' behavioural intentions to use automated shuttles in public transport

1.2. Hypotheses development and model formulation

1.2.1. Direct and indirect relationships between UTAUT2 constructs
The relevance of the UTAUT2 constructs performance expectancy, social influence, hedonic motivation and facilitating conditions to predict behavioural intentions to use automated vehicles has been supported by various studies (Kaur and Rampersad 2018; Madigan et al. 2016; Madigan et al. 2017; Panagiotopoulos and Dimitrakopoulos 2018; Xu et al. 2018). The role of effort expectancy in predicting automated vehicle acceptance has been ambiguous. Madigan et al. (2016) and Wu et al. (2019) supported a positive direct effect of effort expectancy

on behavioural intention, while the effect of effort expectancy on behavioural intention was not significant in the study of Madigan et al. (2017). Panagiotopoulos and Dimitrakopoulos (2018), Wu et al. (2019), and Zhang et al. (2019) reported positive effects of effort expectancy on performance expectancy, which reflects the literature on technology acceptance (Adams, Nelson, and Todd 1992; Chang et al. 2015; Karahanna, Agarwal, and Angst 2006; Venkatesh and Davis 2000). Based on these findings, we propose that the effect of effort expectancy on behavioural intention is mediated through performance expectancy. This suggests that any relationship between people's expectations of how difficult automated shuttles will be to use and their intentions to use them can be explained through their expectations around how these vehicles will perform. In line with the above studies, we define effort expectancy as a positive attribute (i.e., high effort expectancy indicates low effort) and hypothesize:

H1*:* Performance expectancy will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

H2a: Effort expectancy will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

H2b: The effect of effort expectancy on behavioural intention will be mediated through performance expectancy.

H3: Social influence will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

H4: Facilitating conditions will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

H5: Hedonic motivation will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

The examination of the relationships between facilitating conditions, performance expectancy and effort expectancy as well as hedonic motivation has been underrepresented by the literature on automated vehicle acceptance so far. Empirical evidence for these relationships already exists in other domains. Bervell and Umar (2017) applied UTAUT to Learning Management Systems and found significant effects of facilitating conditions on performance expectancy and effort expectancy. It is likely that supportive infrastructure will encourage individuals to come to believe that automated shuttles are useful, easy to use and pleasurable. In Merat et al. (2018), respondents showed a preference for automated shuttles travelling in a designated lane, showing the link between the infrastructure provided and people's attitudes towards automated shuttles. Thus, we hypothesize:

H6: Facilitating conditions will have a positive effect on respondents' ratings of performance expectancy.

H7: Facilitating conditions will have a positive effect on respondents' ratings of effort expectancy.

H8: Facilitating conditions will have a positive effect on respondents' ratings of hedonic motivation.

Venkatesh and Davis (2000) assumed relationships between subjective norm and perceived usefulness. Acheampong and Cugurullo (2019) addressed the interrelationships between the UTAUT constructs and found positive effects of subjective norm (equivalent

to social influence) on the perceived benefits (equivalent to performance expectancy, see Xu et al. 2018; Zhang et al. 2019), and ease of use of automated driving technology (equivalent to effort expectancy), and a positive relationship between subjective norm and perceived behavioural control (equivalent to facilitating conditions). Koenig-Lewis et al. (2015) supported the positive relationship between social influence and perceived usefulness and ease of use. Bervell and Umar (2017) hypothesized positive effects of social influence on performance expectancy, which, however, could not be supported by their data. The authors further revealed a positive relationship between facilitating conditions and social influence. Kumar and Bervell (2019) applied the UTAUT2 model to examine the acceptance of Google classroom and revealed significant relationships between social influence and hedonic motivation. Consequently, we assume a positive relationship between social influence and hedonic motivation. In line with Venkatesh and Davis (2000), the underlying assumptions for all these hypotheses are that if individuals think that people important to them believe they should use automated shuttles, they are more inclined to comply with the referents and believe that automated shuttles are useful, easy to use, that they have the necessary resources, and that automated shuttles are enjoyable. Thus, we hypothesize:

H9: Social influence will have a positive effect on respondents' ratings of performance expectancy.

H10: Social influence will have a positive effect on respondents' ratings of effort expectancy.

H11: Social influence will have a positive effect on respondents' ratings of facilitating conditions.

H12: Social influence will have a positive effect on respondents' ratings of hedonic motivation.

Studies further provided empirical evidence for positive effects of perceived enjoyment (equivalent to our construct hedonic motivation) on perceived usefulness (equivalent to performance expectancy) and perceived ease of use (equivalent to effort expectancy) in the field of technology acceptance (Koenig-Lewis et al. 2015; Teo and Noyes 2011). The underlying assumption is that if automated shuttles are perceived to be enjoyable, individuals will be more inclined to believe that automated shuttles are useful and easy to use. We hypothesize:

H13: Hedonic motivation will have a positive effect on respondents' ratings of performance expectancy.

H14: Hedonic motivation will have a positive effect on respondents' ratings of effort expectancy.

1.3. Car and public transport use

The private car has remained the most attractive mode of transport despite creating serious collective disadvantages, such as traffic congestion, accidents, and environmental pollution (Beirão and Cabral, 2007; Tertoolen, Van Kreveld, and Verstraten 1998). It has been associated with a source of sensation seeking, power, freedom, status, superiority, convenience, speed, comfort, rapidity, and flexibility (Anable and Gatersleben 2005; Beirão and Cabral, 2007; Hagman 2003; Jensen 1999; Steg 2005). We would expect a negative relationship between car use and the intention to use automated shuttles, and a positive relationship between public transport use and the intention to use automated shuttles in public transport. In Nielsen and Haustein (2018), individuals with higher concerns regarding self-driving cars reported a higher

share of driving on a daily basis compared to individuals who were indifferent and enthusiastic towards self-driving cars. Zmud and Sener (2017) found that car users were less likely and users of other modes of transport (e.g., walking, vehicle passengers) more likely to use automated vehicles, and Nazari, Noruzoliaee, and Mohammadian (2018) found a negative relationship between daily vehicle miles travelled and the inclination towards private and shared automated vehicles. It was further found that individuals who frequently travel with non-car travel modes (i.e., public transport, biking, walking) are more likely to be interested in automated vehicle technology. Haboucha, Ishaq, and Shiftan (2017) revealed that individuals who never use public transport were less likely to use shared automated vehicles. This corresponds with Liljamo, Limatainen, and Pöllänen (2018) who found that individuals using public transport and who do not have a car had more positive attitudes towards automated vehicles.

There is still a paucity of knowledge about how car and public transport use affect the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation. Understanding these relationships will help to inform the factors which might increase the likelihood of car drivers being willing to change to automated shuttles. To the best of our knowledge, our study is the first that investigates such a relationship. We hypothesize that individuals who frequently use a car will find automated shuttles in public transport less useful in attaining their mobility needs than individuals who frequently use public transport. The underlying assumption is that reliability, frequency, accessibility, and competitive costs were the frequently cited reasons that motivate car use and discourage the use of public transport (Redman et al. 2013).

We further hypothesize that individuals who frequently use a car find automated shuttles in public transport less easy to use and are less likely to believe that they have the necessary resources to use automated shuttles in public transport than frequent public transport users. This corresponds with Hine and Scott (2000) who found that car users were more concerned about way-finding through an interchange and their need for information about travel than users of public transport.

H15: Car use will have a negative effect on respondents' ratings of performance expectancy.

H16: Car use will have a negative effect on respondents' ratings of effort expectancy.

H17: Car use will have a negative effect on respondents' ratings of facilitating conditions.

H18: Car use will have a negative effect on respondents' ratings of hedonic motivation.

H19: Car use will have a negative effect on respondents' ratings of the behavioural intention to use automated shuttles.

We further expect that car users will find automated shuttles in public transport less enjoyable than frequent users of public transport. Asgari and Jin (2019) provide empirical evidence for a negative relationship between the enjoyment of driving and the adoption of automated vehicles and the willingness to pay for automated driving features. This corresponds with Haboucha, Ishaq, and Shiftan (2017) who found that individuals who enjoy driving a car were more likely to use their regular car than an automated shuttle. We hypothesize:

H20: Public transport use will have a positive effect on respondents' ratings of performance expectancy.

H21: Public transport use will have a positive effect on respondents' ratings of effort expectancy.

H22: Public transport use will have a positive effect on respondents' ratings of facilitating conditions.

H23: Public transport use will have a positive effect on respondents' ratings of hedonic motivation.

H24: Public transport use will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

1.4. Technology savviness

In MAVA, our multi-level model on automated vehicle acceptance, technology savviness is associated with an individual's innovativeness, the number and type of technologies used, curiosity, technology readiness, openness, interest, or optimism (Nordhoff, De Winter, et al. 2019). On the basis of a literature review of surveys about automated vehicles, Gkartzonikas and Gkritza (2019) defined consumer innovativeness as concept that can potentially influence an individual's intention to take a ride in an automated vehicle. In the study of Asgari and Jin (2019), Lavieri et al. (2017) and Shabanpour et al. (2017), tech-savvy individuals were more likely to be early adopters of autonomous vehicles. Nazari, Noruzoliaee, and Mohammadian (2018) found that mobility-on-demand (MOD) savviness (i.e., owning a smartphone, frequency of using app-based carsharing and ride-sourcing) was positively correlated with an interest in automated vehicle technology, and an interest in commuting with automated vehicles. These studies provide empirical evidence for a positive relationship between technology savviness and the intention to use automated vehicles.

While there is empirical evidence for the relationship between technology savviness and behavioural intention, there is still limited understanding of how technology savviness is related to the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation. Bansal, Kockelman, and Singh (2016) found more positive attitudes towards automated vehicle technologies among technology-savvy individuals. We hypothesize that tech-savvy individuals will be more likely to consider automated shuttles useful (i.e., performance expectancy), and enjoyable (i.e., hedonic motivation) because they are more open towards and interested in new technologies and more likely to see the added value of automated shuttles. Furthermore, due to their technology affinity, they are more likely to believe they have the necessary resources to use automated shuttles (i.e., facilitating conditions), and that it is easy to learn how to use automated shuttles (i.e., effort expectancy). As they are more likely to be surrounded with like-minded peers, they are also more likely to believe that people important to them will appreciate their use of automated shuttles (i.e., social influence). We hypothesize:

H25: Technology savviness will have a positive effect on respondents' ratings of performance expectancy.

H26: Technology savviness will have a positive effect on respondents' ratings of effort expectancy.

H27: Technology savviness will have a positive effect on respondents' ratings of social influence.

H28: Technology savviness will have a positive effect on respondents' ratings of facilitating conditions.

H29: Technology savviness will have a positive effect on respondents' ratings of hedonic motivation.

H30: Technology savviness will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

1.5. Automated shuttle experience

The intention to use automated vehicles is a function of an individual's knowledge of and experience with automated vehicles (Nordhoff, De Winter, et al. 2019). Berliner, Hardman, and Tal (2019) found that individuals who reported a higher level of knowledge of automated vehicles were more interested in purchasing them. The scientific literature further supports the relationship between automated vehicle experience, performance expectancy and effort expectancy. Liu, Guo, et al. (2019) found that individuals who heard of self-driving vehicles gave higher ratings to the perceived benefits of automated vehicles (equivalent to performance expectancy), and to items that pertain to the trust in automated vehicles, while they gave lower ratings to the perceived dread and perceived risks of automated vehicles. This corresponds with Liu, Xu, et al. (2019) who found that respondents' ratings of positive affect, perceived benefit, acceptance of road tests and social trust increased, while their ratings of negative affect and perceived risk decreased. Xu et al. (2018) revealed that experience with automated vehicles increased the perceived usefulness and ease of use of automated vehicles, and increased the strength of the effects of perceived usefulness and ease of use on individuals' intentions to use automated vehicles. These findings correspond with research on the determinants of electronic health records where experience had positive effects on the perceived usefulness and ease of use (Tubaishat 2017). While empirical research supports the relationship between automated shuttle experience, performance expectancy, effort expectancy and behavioural intention, there is a paucity of knowledge on how experience affects the UTAUT2 constructs facilitating conditions and hedonic motivation. We hypothesize:

H31: Experience with automated shuttles will have a positive effect on respondents' ratings of performance expectancy.

H32: Experience with automated shuttles will have a positive effect on respondents' ratings of effort expectancy.

H33: Experience with automated shuttles will have a positive effect on respondents' ratings of facilitating conditions.

H34: Experience with automated shuttles will have a positive effect on respondents' ratings of hedonic motivation.

H35: Experience with automated shuttles will have a positive effect on respondents' ratings of the behavioural intention to use automated shuttles.

2. Method

2.1. Automated shuttle, route and procedure

The demonstration involved six automated shuttles from the French company Robosoft that operated on a dedicated lane on a route of 2.5 km with eight stops in the Trikala city

centre in Greece. The shuttle carried up to 10 passengers per trip and ran at an average speed of around 13 km/h. A steward was on board the shuttle to intervene in the shuttle operations when requested by the automated driving system. A purposive sample was drawn among individuals who used the automated shuttle at least once during the demonstration in order to ensure that only individuals with some knowledge of these shuttles entered the sample. Respondents filled out the questionnaire on tablet computers that were administered by members of staff from E-Trikala. The information was recorded anonymously and no financial compensation was offered to respondents. An image of the automated shuttle that was deployed in the CityMobil2 demonstration is provided in Figure 1.

2.2. Instrument

The design of the 57-item questionnaire, which was adopted from the study of Madigan et al. (2017), was informed by interviews that were conducted in Leeds, U.K. and Braunschweig, Germany. The questionnaire items were translated into Greek by members of the E-Trikala team, and the translation was checked independently by the Institute of Communication and Computer Systems (ICCS) in Greece and a bilingual colleague in England. The study variables are based on established scales from the technology acceptance management literature, including an earlier study on the acceptance of automated shuttles that operated in La Rochelle in France and Lausanne in Switzerland (Madigan et al. 2016) as shown by Table 1.

2.3. Analysis of responses

Following the recommendations of Anderson and Gerbing (1988), a two-step approach was adopted. In the first step, a confirmatory factor analysis was performed to evaluate the measurement model. This step involves estimating the measurement relationships between the observed variables and their underlying latent variables. Latent variables are theoretical or hypothetical constructs that are not directly measured, which is why they are commonly described as unobserved variables. Latent variables can either be exogenous (i.e., independent), or endogenous (i.e., dependent) variables. The latent exogenous variables in our measurement model are social influence (SI) and facilitating conditions (FC), while the latent endogenous variables are performance expectancy (PE), effort expectancy (EE), hedonic motivation (HM), and behavioural intention (BI). Latent variables are indirectly

Figure 1. Automated shuttle by Robosoft on a public road in a mixed traffic situation in Trikala, Greece.

Table 1. Measurement of study variables.

Construct	Measurement	Source
Performance expectancy (PE)	PE1: I find the ARTS a useful mode of transport. PE2: Using the ARTS to travel helps me to achieve things that are important to me.	Davis, 1989; Madigan et al. 2016; Venkatesh, Thong, and Xu 2012
Effort expectancy (EE)	EE1: My interaction with the ARTS is clear and understandable. EE2: I find the ARTS easy to use EE3: Learning to use an ARTS is easy for me.	Davis, 1989; Madigan et al. 2016; Venkatesh, Thong, and Xu 2012
Social influence (SI)	SI1: People who are important to me think that I should use ARTS. SI2: People who influence my behavior think that I should use ARTS. SI3: People whose opinions I value would like me to use ARTS.	Davis, 1989; Madigan et al. 2016; Venkatesh, Thong, and Xu 2012
Facilitating conditions (FC)	FC1: I have the resources necessary to use ARTS. FC2: I have the knowledge necessary to use ARTS.	Davis, 1989; Madigan et al. 2016; Venkatesh, Thong, and Xu 2012
Hedonic motivation (HM)	HM1: Using ARTS is fun. HM2: Using ARTS is entertaining. HM3: Using ARTS is enjoyable.	Davis, 1989; Madigan et al. 2016; Venkatesh, Thong, and Xu 2012
Behavioural intention (BI)	BI1: Assuming that I had access to ARTS, I predict that I would use it in the future. BI2: If ARTS become available permanently, I plan to use it. BI3: I intend to use ARTS again during the demonstration period.	Davis, 1989; Madigan et al. 2016; Venkatesh, Thong, and Xu 2012
Car use (CU)	CU1: Days a week using a car	Welch, 2015
Public transport use (PTU)	PTU1: Days a week using any form of public transport	
Technology savviness (TS)	TS1: When it comes to trying a new technology product, I am generally: a) among the last, b) in the middle, c) among the first.	Merat and Barnard 2010; Merat et al. 2018
Automated shuttle experience (AS–EXP)	AS–EXP1: Number of interactions with the automated shuttle AS–EXP2: Number of times using the automated shuttle	Karahanna, Agarwal, and Angst 2006

measured by observed or manifest variables that are directly measured (i.e., questionnaire items). Observed variables can also be exogenous and endogenous (Raykov and Marcoulides 2006). The observed exogenous variables are SI1–SI3 and FC1–FC2, while the observed endogenous variables in our measurement model include PE1–PE2, EE1–EE3, HM1–HM3, and BI1–BI3 (see Table 2 for descriptions). The psychometric properties of the measurement model were assessed by its indicator reliability, internal consistency reliability, convergent validity and discriminant validity. Convergent validity was assessed by four criteria: (1) All scale items should be significant and have loadings exceeding 0.70 on their respective scales, (2) the average variance extracted (AVE) should exceed 0.50, (3) composite reliability (CR) should exceed 0.70, and (4) Cronbach's alpha values should be greater than 0.70 (Anderson and Gerbing 1988; Fornell and Larcker 1981). Discriminant validity of our data was examined with the test of squared correlations by Anderson and Gerbing (1988), which implies that the correlation coefficient between two latent variables is smaller than the square root of the average variance extracted (AVE) of each latent variable.

In the second step of our analysis, a structural equation model, which relates the latent and observed variables to each other, was built in order to test the hypotheses H1–H36 and determine the weighting factors in order to quantify the strength of the relationships between our latent variables (Chau 1997). Covariance-based structural equation modelling was used in this

Table 2. Descriptive statistics and results of the confirmatory factor analysis.

Latent variable	Observed variable	M	SD	λ	p-value	αv > 0.7	CR > 0.7	AVE > 0.5	VIF < 3.3
Performance expectancy (PE)	PE1: I find the ARTS a useful mode of transport.	3.62	0.84	0.83		0.77	0.78	0.64	2.36
	PE2: Using the ARTS to travel helps me to achieve things that are important to me.			0.77	0.000				
Effort expectancy (EE)	EE1: My interaction with the ARTS is clear and understandable.	3.92	0.71	0.81		0.88	0.89	0.72	1.70
	EE2: I find the ARTS easy to use.			0.91	0.000				
	EE3: Learning to use an ARTS is easy for me.			0.83	0.000				
Social influence (SI)	SI1: People who influence my behaviour think that I should use ARTS.	3.37	0.79	0.83		0.89	0.89	0.74	2.22
	SI2: People who are important to me think that I should use ARTS.			0.89	0.000				
	SI3: People whose opinions I value would like me to use ARTS.			0.85	0.000				
Facilitating conditions (FC)	FC1: I have the resources necessary to use ARTS.	3.91	0.75	0.84		0.85	0.84	0.73	1.97
	FC2: I have the knowledge necessary to use ARTS.			0.87	0.000				
Hedonic motivation (HM)	HM1: Using ARTS is fun.	3.82	0.74	0.84		0.87	0.87	0.68	2
	HM2: Using ARTS is entertaining.			0.86	0.000				
	HM3: Using ARTS is enjoyable.			0.79	0.000				
Behavioural intention (BI)	BI1: Assuming that I had access to ARTS, I predict that I would use it in the future.	3.74	0.74	0.80		0.90	0.90	0.75	–
	BI2: If ARTS become available permanently, I plan to use it.			0.90	0.000				
	BI3: I intend to use ARTS again during the demonstration period.			0.89	0.000				
CFI				0.97					
RMSEA				0.06					
SRMR				0.03					
χ^2/df				2.26					

Note: M = Mean, SD = Standard deviation, λ = Lambda, factor loading, α = Cronbach alpha, CR = Composite reliability, AVE = Average variance extracted, VIF = Variance inflation factor, ARTS = Automated Rapid Transit Systems.

study as it is the default technique in R software lavaan package to run the structural equation models. It is the most prevalent technique and is best suited for confirmatory rather than exploratory factor analyses and theory development (Hair et al. 2014; Hair, Ringle, and Sarstedt 2011). In this step, car and public transport use, technology savviness, and automated shuttle experience were added to the model to investigate their relationships with the latent variables.

Structural equation modelling is a powerful technique for multivariate data techniques that is particularly suited to investigating multiple indirect and direct effects among variables and to assess the convergence between a theoretical model and empirical data. Evaluating the structural model involves estimating the path coefficients (i.e., standardized regression weights), which indicate the strengths of the relationships between the variables, their level of significance, and the R–square values (i.e., amount of variance explained) (Backhaus, Erichson, and Weiber 2015). Maximum likelihood estimation (MLE) was used for this calculation. To deal with missing data, we used Full Information Maximum Likelihood (FIML), which is deemed to be superior to other methods of missing data treatment (Schafer and Graham 2002).

With 315 respondents our study meets the suggested minimum sample size requirement of 100 to achieve adequate power in MLE technique (Hair et al. 1998). Multiple fit indices will be reported to account for the weaknesses inherent in different indices: *Comparative Fit Index* (CFI) ≥ 0.90, *Root Mean Square Error of Approximation* (RMSEA) ≤ 0.08, and the *Standardized Root Mean Square Residual* (SRMR) ≤ 0.06 (Hair et al. 2014; Hooper, Coughlan, and Mullen 2008; Hu and Bentler 2009; Schreiber et al. 2006). Structural equation modelling was performed with the R package *lavaan* 0.5–20 (Rosseel 2012).

2.4. Respondents

315 participants completed the questionnaire between December 2015 and February 2016, of which 54.6% were male and 45.4% female. Respondents had an average age of 33.35 years (SD = 10.76). Most of the respondents used the automated shuttle twice ($M = 2.23$, SD = 1.39), and interacted with it three or four times ($M = 3.64$, SD = 1.60). Respondents' reported car use was on average four days a week ($M = 3.92$, SD = 2.90, Min = 0, Max = 22), and their reported public transport use was on average two days a week ($M = 2.05$, SD = 5.45, Min = 0, Max = 85). For technology savviness, 36.82% of respondents rated themselves among the first trying a new technology product, 46.35% in the middle, and 16.83% among the last.

3. Results

3.1. Confirmatory factor analysis

The measurement model consists of the six latent variables performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating conditions and behavioural intention and their underlying observed variables.

The descriptive statistics of our latent variables and the results of the confirmatory factor analysis are shown in Table 2. Note that we used the same operationalization of our study constructs that was applied in the study of Madigan et al. (2017). Model fit parameters were acceptable for all latent variables (see Table 2).

All scale items exceeded the recommended threshold of 0.7 and were statistically significant. Composite reliability and Cronbach's alpha both exceeded the recommended threshold of 0.7, confirming internal consistency reliability. Cronbach's alpha and

Table 3. Inter-construct correlation matrix.

Construct	Performance expectancy	Effort expectancy	Social influence	Facilitating conditions	Hedonic motivation	Behavioural intention
Performance expectancy	**0.80**					
Effort expectancy	0.62	**0.85**				
Social influence	0.44	0.38	**0.86**			
Facilitating conditions	0.54	0.68	0.33	**0.79**		
Hedonic motivation	0.51	0.69	0.45	0.64	**0.82**	
Behavioural intention	0.60	0.59	0.51	0.59	0.68	**0.87**

Note: The diagonal values represent the square root of the average variance extracted (AVE).

composite reliability for the entire instrument were 0.93 and 0.97, respectively. The average variance extracted (AVE) values exceeded the recommended threshold of 0.5 for all latent variables, ranging between 0.64 and 0.74. The variance inflation factors (VIFs) of our latent constructs reported in Table 2 are all below 3.3, which represents an accepted rule of thumb to rule out multi-collinearity (Hair et al. 2017; Kline 2015; Kock 2015). As shown by Table 3, which reports the Pearson correlations between the constructs, discriminant validity was acceptable for all latent variables.

3.2. Structural model testing

We ran two structural models as presented in Table 4, and the significant relationships of the most advanced (second) model are shown in Figure 2.
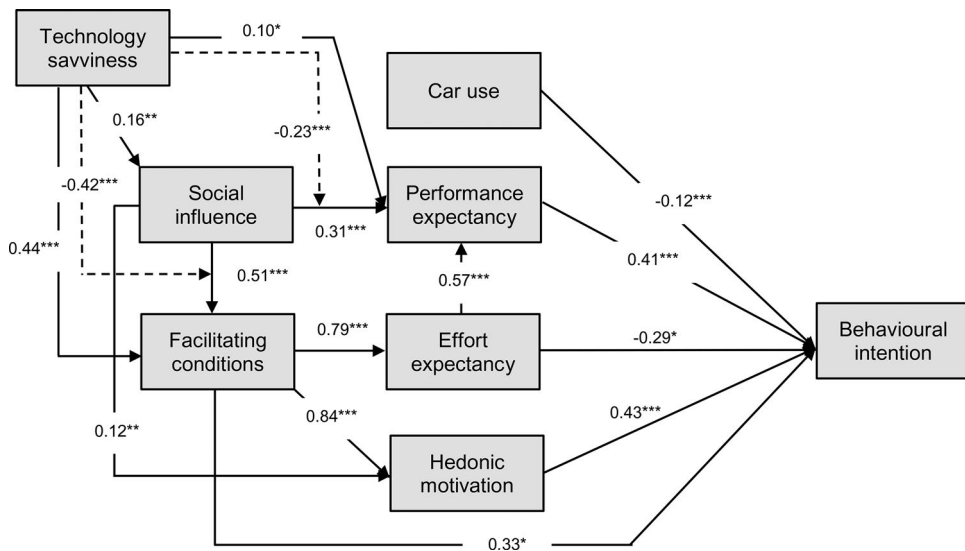

Figure 2. Significant structural path relationships in second model. Dashed arrows denote moderation effects.

Table 4. Structural equation models: hypothetical path, standardized path coefficients (β), and variance explained (R^2).

Hypothetical path	First model: Effect β	Confidence interval 5%	95%	Second model: Effect β	Confidence interval 5%	95%
H1: Performance expectancy → behavioural intention (b)*	0.37***	0.127	0.423	0.41***	0.139	0.390
H2a: Effort expectancy → behavioural intention (c)*	-0.23, n.s.	-0.443	0.007	-0.29*	-0.506	-0.046
H2b: Effort expectancy → performance expectancy (a)*	0.66***	0.575	1.135	0.51***	0.414	1.084
H2b: Indirect effect = a* b	0.24**	0.078	0.391	0.22**	0.060	0.349
H2b: Total = c + (a* b)	0.02, n.s.	-0.153	0.187	-0.08, n.s.	-0.290	0.139
H3: Social influence → behavioural intention	0.12*	0.004	0.201	0.09, n.s.	-0.003	0.211
H4: Facilitating conditions → behavioural intention	0.21*	0.023	0.370	0.33*	0.010	0.592
H5: Hedonic motivation → behavioural intention	0.48***	0.256	0.604	0.43***	0.195	0.579
H6: Facilitating conditions → performance expectancy	0.17, n.s.	-0.058	0.479	-0.25, n.s.	0.106	0.795
H7: Facilitating conditions → effort expectancy	0.47***	0.296	0.617	0.79***	0.552	0.947
H8: Facilitating conditions → hedonic motivation	0.67***	0.566	0.831	0.84***	0.732	0.954
H9: Social influence → performance expectancy	0.27***	0.176	0.450	0.31***	0.409	0.757
H10: Social influence → effort expectancy	0.01, n.s.	-0.080	0.096	-0.00, n.s.	-0.100	0.093
H11: Social influence → facilitating conditions	0.37***	0.227	0.454	0.51***	0.562	0.796
H12: Social influence → hedonic motivation	0.24***	0.134	0.336	0.12**	0.054	0.277
H13: Hedonic motivation → effort expectancy	0.42***	0.231	0.548	0.17, n.s	-0.028	0.347
H14: Hedonic motivation → performance expectancy	-0.13, n.s.	-0.414	0.099	-0.18, n.s.	-0.536	0.039
H15: Car use → performance expectancy	-0.03, n.s.	-0.036	0.018	-0.02, n.s.	-0.037	0.018
H16: Car use → effort expectancy	-0.01, n.s.	-0.020	0.016	-0.02, n.s.	-0.023	0.012
H17: Car use → facilitating conditions	0.08, n.s.	-0.009	0.043	0.04, n.s.	-0.010	0.038
H18: Car use → hedonic motivation	-0.08, n.s.	-0.040	0.002	-0.06, n.s.	-0.039	0.002
H19: Car use → behavioural intention	-0.16***	-0.053	-0.018	-0.12***	-0.054	-0.018
H20: Public transport use → performance expectancy	-0.03, n.s.	-0.019	0.010	-0.02, n.s.	-0.019	0.010
H21: Public transport use → effort expectancy	0.01, n.s.	-0.008	0.011	0.02, n.s.	-0.006	0.012
H22: Public transport use → facilitating conditions	-0.09, n.s.	-0.025	0.002	-0.06, n.s..	-0.024	0.002
H23: Public transport use → hedonic motivation	0.03, n.s.	-0.008	0.015	0.03, n.s.	-0.006	0.016
H24: Public transport use → behavioural intention	0.00, n.s.	-0.009	0.009	0.00, n.s.	-0.009	0.009
H25: Technology savviness → performance expectancy	-0.12*	-0.254	-0.028	0.10*	0.045	0.340
Interaction of social influence × technology savviness → performance expectancy	–	–	–	-0.23***	-0.137	-0.070
H26: Technology savviness → effort expectancy	−0.00, n.s.	−0.076	0.073	-0.01, n.s.	-0.100	0.071

Table 4. (Continued)

H27: Technology savviness → social influence	0.16**	0.040	0.277	0.16**	0.040	0.277
H28: Technology savviness → facilitating conditions	0.20**	0.080	0.293	0.44***	0.492	0.699
Interaction of social influence × technology savviness → facilitating conditions	–	–	–	-0.42***	-0.155	-0.107
H29: Technology savviness → hedonic motivation	0.04, *n.s.*	-0.051	0.128	0.01, *n.s.*	-0.083	0.119
H30: Technology savviness → behavioural intention	0.02, *n.s.*	-0.058	0.090	0.01, *n.s.*	-0.071	0.097
H31–1: Number of interactions → performance expectancy	-0.03, *n.s.*	-0.068	0.034	-0.02, *n.s.*	-0.066	0.037
H32–1: Number of interactions → effort expectancy	0.06, *n.s.*	-0.011	0.055	0.05, *n.s.*	-0.006	0.059
H33–1: Number of interactions → facilitating conditions	-0.08, *n.s.*	-0.081	0.015	-0.04, *n.s.*	-0.067	0.023
H34–1: Number of interactions → hedonic motivation	0.08, *n.s.*	-0.005	0.074	0.05, *n.s.*	-0.007	0.069
H35–1: Number of interactions → behavioural intention	-0.05, *n.s.*	-0.051	0.014	-0.03, *n.s.*	-0.050	0.015
H31–2: Number of uses → performance expectancy	0.07, *n.s.*	-0.018	0.099	0.04, *n.s.*	-0.019	0.097
H32–2: Number of uses → effort expectancy	-0.06, *n.s.*	-0.064	0.012	-0.03, *n.s.*	-0.056	0.019
H33–2: Number of uses → facilitating conditions	-0.06, *n.s.*	-0.087	0.025	-0.04, *n.s.*	-0.067	0.023
H34–2: Number of uses → hedonic motivation	-0.01, *n.s.*	-0.052	0.041	0.01, *n.s.*	-0.041	0.047
H35–2: Number of uses → behavioural intention	0.06, *n.s.*	-0.011	0.064	0.04, *n.s.*	-0.010	0.065
CFI		0.96			0.66	
RMSEA		0.06			0.19	
SRMR		0.05			0.25	
χ^2/df		1.96			12.13	
R^2 of BI		0.719			0.856	
R^2 of PE		0.667			0.881	
R^2 of EE		0.699			0.879	
R^2 of FC		0.219			0.699	
R^2 of SI		0.024			0.024	
R^2 of HM		0.639			0.853	

Notes: $^*0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. *n.s.* = not significant

In the first structural model, the main effects of the UTAUT2 constructs, car and public transport use, technology savviness and automated shuttle experience on the behavioural intention to use automated shuttles and the interrelationships between these constructs were investigated. It was further investigated to what extent the relationship between effort expectancy and behavioural intention was mediated by performance expectancy.

Technology savviness had significant relationships with social influence, facilitating conditions, and performance expectancy in the first model. Therefore, in a second structural model, we investigated whether the relationships between (1) social influence and facilitating conditions, and (2) social influence and performance expectancy is moderated by technology savviness. Therefore, we created mean-centred interaction terms of social influence and technology savviness. As shown by Table 4, the moderation analysis revealed that the relationships between social influence and facilitating conditions and social influence andv performance expectancy were moderated by technology savviness.

4. Discussion

The present study enhanced our understanding of the factors influencing automated shuttle acceptance and their interrelationships. Structural equation modelling was used to investigate the direct and indirect effects of the UTAUT2 constructs on the behavioural intention to use automated shuttles.

4.1.1. Direct and indirect relationships between UTAUT2 constructs

In line with Madigan et al. (2017), who used the same dataset, hedonic motivation was the strongest predictor of individuals' behavioural intentions to use automated shuttles in public transport before and after adding car and public transport use, technology savviness and automated shuttle experience to the model.

The majority of research studies on automated vehicle acceptance, including the study of Madigan et al. (2017), examined the direct effects of the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions and hedonic motivation on individuals' behavioural intentions to use automated shuttles. This study also examined the indirect effects of the UTAUT2 constructs by their interrelationships. Unlike Madigan et al. (2017), the present study also considered the influence of car and public transport use, technology savviness and automated shuttle experience on behavioural intention. Furthermore, this study investigated to what extent the relationship between effort expectancy and behavioural intention was mediated by performance expectancy. This provides additional insights outlining the ways in which the various acceptance constructs interact to inform individuals' decisions about whether to use automated shuttles in the future (see Figure 2).

Both Madigan et al. (2017) and the present study found a positive correlation between effort expectancy and behavioural intention in a bivariate correlation context (see Table 3). Our study has revealed that the effect of effort expectancy on behavioural intention was mediated by performance expectancy when the interaction effect between social influence and technology savviness was included in the model (second model). Technology savviness was a negative moderator of the relationship between social influence and facilitating conditions and between social influence and performance expectancy, implying that these relationships are weaker for tech-savvy individuals. This suggests that tech-savvy individuals rely less on their social networks to nurture their beliefs that automated shuttles are useful and to have the necessary resources to use automated shuttles. This finding is not counter-intuitive as tech-savvy individuals may have more positive beliefs regarding the expected benefits of automated shuttles and sufficient confidence in their skills and capabilities to use automated shuttles.

4.1.2. Car and public transport use

Car use was a negative predictor of the behavioural intention to use automated shuttles in public transport. This suggests that car users might be among the customer segments with more negative views towards automated shuttles in public transport. This finding corresponds with research studies, which have revealed that car users expressed a lower interest to use and buy automated vehicles and were less likely to use public transport (Berliner, Hardman, and Tal 2019; Krueger, Rashidi, and Rose 2016; Nordfjærn et al. 2015).

The effects of public transport use on the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and behavioural intention were not significant. This contradicts the study of Haboucha, Ishaq, and Shiftan (2017) who found a negative relationship between public transport use and the use of a shared automated vehicle.

4.1.3. Technology savviness

The positive relationships between technology savviness and social influence as well as between technology savviness and facilitating conditions correspond with Acheampong and Cugurullo (2019). Our findings suggest that tech-savvy individuals are more likely to believe they are in possession of the necessary resources to use automated shuttles and that people important to them will appreciate their use of automated shuttles.

The positive relationship between technology savviness and performance expectancy in the second model suggests that technology-savvy individuals are more likely to consider automated shuttles useful. This finding corresponds with the literature on automated vehicle acceptance that reports a positive relationship between technology savviness and attitudes towards automated vehicles (Bansal, Kockelman, and Singh 2016; Lavieri et al. 2017).

4.1.4. Automated shuttle experience

Automated shuttle experience did not exert a positive effect on automated vehicle acceptance. This corresponds with studies which found that familiarity with automated shuttles did not predict willingness to pay for automated vehicles (Bansal and Kockelman 2018), and did not show positive effects on support for automated vehicles (Distler, Lallemand, and Bellet 2018; Dixon et al., 2018). However, studies also reveal that experienced and knowledgeable individuals were more positive towards automated vehicles, and more likely to intend to use them in comparison to less experienced and knowledgeable individuals (Liu, Xu, et al. 2019). Most of the studies on automated vehicle acceptance are based on respondents' knowledge (e.g., knowledge respondents gain in the context of the study, through media, other information channels, friends/colleagues) rather than direct physical experience with automated vehicles (Nordhoff, De Winter, et al. 2019). Tennant, Stares, and Howard (2019) pointed to the difficulties in researching public opinions towards automated vehicles, and posited that it is speculative to assume that public unease will decline as people become more familiar with automated vehicles. Dixon et al. (2020) suggested that simply experiencing automated vehicles will be ineffective in establishing automated vehicle acceptance.

4.2. Recommendations for future research

First, we recommend future research to evaluate whether the pleasure of being driven (or hedonic motivation in more scientific terms) can be enhanced by the possibility for travellers to engage in on-board, non-driving related activities. Research has demonstrated that a positive utility can be derived from using public transport due to the commuters' ability to listen to music or audio books, browse the internet, enjoy the scenery, talk on the phone, sleep, think and relax (Handy, Weston, and Mokhtarian 2005; Larson 1998; Mokhtarian and Salomon 2001;

Salomon and Mokhtarian 1997). Pudāne et al. (2019) proposed that the availability of automated vehicles/limited planning, travel continuity, and comfort have a positive impact on the perceived pleasure of travelling in automated vehicles. More research is necessary to disentangle the relationship between these characteristics and driving pleasure. This shall include trust in automation and perceived safety, which are key factors in the acceptance of automated driving (Choi and Ji 2015; Nordhoff, De Winter, et al. 2019; Zhang et al. 2019).

Second, automated shuttles in public transport will cover small to medium distances between public transport nodes and individuals' destinations (i.e., trips to or from public transport stations). Consequently, the ability and willingness to pursue recreational or work-related activities may be limited and the full potential of automated shuttles in public transport not leveraged. Future research should address the various user needs along different parts of the journey that most likely yield different implications for vehicle manufacturers, designers, operators and mobility providers to effectively market automated shuttles (Yap, Correira, and Van Arem 2015). In particular, it should be investigated which attributes of automated shuttles in public transport attract car users in order to encourage a modal shift.

Third, future research should focus on identifying additional constructs such as a person's personality (Madigan et al. 2016; Yap, Correira, and Van Arem 2015) and macro-level factors (Nordhoff, De Winter, et al. 2019) to investigate whether these factors can increase the explanatory power of our model and account for the remaining variance in behavioural intention.

Fourth, future research should investigate whether it is reasonable to merge the constructs effort expectancy and facilitating conditions given (1) the ambiguous role of effort expectancy in research on the acceptance of automated vehicles as highlighted before, and (2) the relatively strong relationship between effort expectancy and facilitating conditions that was detected in our study. Zoellick et al. (2019) did not use perceived ease of use (i.e., equivalent of effort expectancy) as latent construct in their analysis due to the difficulties to apply it to the context of automated public transport, and Madigan et al. (2017) proposed to exclude effort expectancy from future studies as it was not a significant predictor of the intentions to use automated shuttles. The current study provides further evidence of the difficulties in understanding how effort expectancy might link to automated technology use. A possible explanation is that respondents are not well able to discriminate between effort expectancy, performance expectancy and facilitating conditions. Furthermore, we encourage researchers to revisit the operationalization of facilitating conditions. The items measuring facilitating conditions are usually expressed in very generic terms (i.e., resources, knowledge), leaving ample room for respondents to speculate on the meaning of this construct and attach different meanings to it, which can bias the true effects of facilitating conditions on behavioural intention.

Fifth, we recommend future research to revisit the relationship between automated shuttle experience and acceptance, making more use of experienced versus non-experienced individuals (Tennant, Stares, and Howard 2019), and examine not only the amount but also the qualitative experience influencing important aspects of automated vehicle acceptance, such as symbolic-affective (e.g., pleasure, comfort), and domain-specific factors (e.g., performance expectancy and effort expectancy, compatibility; Nordhoff et al., under review).

Sixth, studies modelled technology savviness as a function of individual demographics, household composition, commute characteristics, and new technology usage (Bansal, Kockelman, and Singh 2016; Lavieri et al. 2017). We encourage future research to investigate the relationship between technology savviness and the UTAUT2 constructs, using multiple-item scales (see

Section 4.6.) to better understand the specific nature of technology savviness, and the consequences of its operationalization for its relationship with technology acceptance constructs.

4.3. Implications for policy and practice

The study yields important implications for policy and practice.

First, the strong positive effect of hedonic motivation on behavioural intention suggests that one possible strategy to promote the uptake of automated shuttles is to make travelling with automated shuttles enjoyable, for instance, through high comfort levels. Furthermore, vehicle manufacturers, public transport companies, operators, policy-makers and the media should advertise the benefits of travelling with automated shuttles and emphasize the hedonic aspects, transforming the "pleasure of driving" – a prominent marketing slogan to increase the attractiveness of the car (BMW 2013) – into the "pleasure of *being* driven".

Second, we found strong positive effects of facilitating conditions on effort expectancy and hedonic motivation. These findings imply that a supportive infrastructure is more likely to give rise to a positive opinion about automated shuttles in terms of perceived enjoyment and ease of use. A supportive infrastructure could encompass the provision of accessibility to the shuttle using a wheelchair ramp, ensuring an uncomplicated booking and payment process (e.g., including the use of automated vehicles in public transport tickets), and offering information on routes and interchanges either in or outside the shuttle, in close proximity to the stations, and via an app (Nordhoff, De Winter, et al. 2019). The strong positive effect of effort expectancy on performance expectancy implies that the complexity of using automated shuttles should be reduced and the clarity of the interaction between humans and automated shuttles increased (Zhang et al. 2019).

Third, in line with the findings of König and Neumayr (2017), who over-sampled car-users in their study (i.e., 442 car users versus 47 non-car users), educating car users about the functions, benefits and limitations of the technology in terms of free test rides, comprehensive explanations prior to usage, and free/cheap courses could be a practical method by which the resistance to automated shuttles among car-users could be overcome. Sparrow and Howard (2017) posit that the combination of a rail network with a fleet of autonomous vehicles serving passengers arriving at and departing from each station and offering a door-to-door public transport service could solve the first and last mile problem, thus catering to the needs and preferences of car users.

Fourth, in order to enhance technology savviness, policy makers, manufacturers and public transport companies should develop strategies to identify the segments who are more amenable to adoption (Pettigrew, Dana, and Norman 2019). Opportunities for trial should be offered to increase the visibility of usage (Pettigrew, Dana, and Norman 2019).

4.4. Study limitations

First, the automated shuttle in this study operated at a low speed, on a dedicated route with fixed stops that had to be shared by multiple passengers at the same time.

Second, car and public transport use, technology savviness and automated shuttle experience were measured by single-item scales, which is a limitation in scientific research (Wanous, Reichers, and Hudy 1997). Future research should use multiple-item scales, e.g., similar to the scales in the studies of Asgari and Jin (2019), Bansal, Kockelman, and Singh

(2016), Haboucha, Ishaq, and Shiftan (2017), Lee and Mirman (2018), and Nazari, Noruzoliaee, and Mohammadian (2018).

Third, while structural equation models are useful to model complex relationships between latent and observed variables, the ability to make causal inferences and establish a clear temporal precedence using cross-sectional data is limited (Bagley and Mokhtarian 2002). (Quasi-) experimental studies that measure individuals' opinions before and after they are exposed to automated shuttles should be performed, varying attributes of the transport offered, because they are more suitable to isolate the causes from the effects and thus determine the temporal, cause-effect nature of the relationships between two or more variables (Gould and Golob 1998).

4.5. Final conclusions

The present study investigated the interrelationships between the UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation to add to existing research on automated vehicle acceptance that mainly considered the UTAUT2 constructs as independent antecedents of individuals' behavioural intentions to use automated shuttles. In the first structural model, fifteen of thirty-five hypotheses could be sustained, while the second structural model sustained thirteen of thirty-five hypotheses. Our analysis has revealed that hedonic motivation was the strongest predictor of the behavioural intention to use automated shuttles, followed by performance expectancy and social influence. The relationship between effort expectancy and behavioural intention was mediated by performance expectancy. This implies that people's expectations of how difficult automated shuttles will be to use and their intentions to use them can be explained through their expectations around how these vehicles will perform. The relationships between social influence and facilitating conditions and between social influence and performance expectancy, respectively, were moderated by technology savviness. Individuals with a low technology savviness were less likely to believe that they have the necessary resources to use automated shuttles or that automated shuttles are useful than individuals with a high technology savviness. Car use was a negative predictor of the behavioural intention to use automated shuttles in public transport. We expect that the findings obtained in this study provide useful insights for policy-makers, vehicle manufacturers, public transport companies, operators and designers to inform the design and implementation of automated shuttles.

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Disclosure statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

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