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The central role of trust and perceived risk in the acceptance of autonomous vehicles in an integrated UTAUT model

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Abstract

The adoption of autonomous vehicles (AVs) is crucial for the future of transport. Among their many benefits, one of the most important is increased safety. Yet a key barrier to consumer adoption is the perceived level of risk. In our research, we explore this controversy within the framework of the U*nified Theory of Acceptance and Use of Technology* (UTAUT) model including two key variables: trust and perceived risk. Based on a survey, we tested our hypotheses using structural equation modelling (SEM). Our results suggest that positive perceptions of technology attributes alone—performs well, no effort to use, supported—are not sufficient for acceptance; it is also essential that these attributes increase trust in AVs and thereby reduce perceived risk. If potential users have confidence in AVs and thus perceive a reduced risk, the perceived benefits of the technology can be significantly enhanced. We draw implications for theory and practice from our results, concentrating mainly on the potential to enhance trust in AVs.

Keywords Autonomous vehicles, Acceptance, UTAUT model, Trust, Risk

1 Introduction

Research into user acceptance of autonomous vehicles (AVs) is becoming an increasingly important topic as the technology becomes mainstream. The adoption of AVs can help solve global challenges such as responding to changing consumer needs in metropolitan areas, overcoming environmental problems, making urban environments more efficient through better planned traffic management, or reorganising on-demand capacity [6, 10, 42, 63]. Elements of the vehicle are still under development, however, as they raise both consumer issues and technological issues that need to be addressed. For this reason, interest in AVs has increased in academia worldwide over the last decade. Beyond technological and engineering analyses, societal and economic issues have come to the fore, such as scenario analysis for the next 10 years of self-driving vehicles [48], the tourism potential of AVs [18], and the identification of barriers to and drivers for the use of AVs by consumers [11, 27, 36].

Authors have typically measured consumer intention to use vehicles using the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [35]. Then, in recent years, a growing body of research began to incorporate the perceived risk factor of vehicle use into models [69, 70, 73]. These studies share the suggestion that perceived risk and trust factors may play a central role in technology adoption. Vehicle manufacturers also believe that the adoption of AVs will need to handle these factors, as they can act as barriers [36, 62]. While environmental conditions, social influence, and early adopters of the technology may shape how inhibiting factors are overcome in the future, their place in the model is still questionable [1].

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Although Wang et al. [67] showed in their meta-analysis that almost 60% of accidents could be prevented by using AVs, the intention to adopt the technology by users is still very low [38]. User acceptance of AVs does not necessarily depend on the real benefits and risks of the technology, but rather on their perceptions. Interestingly, the majority of consumers reject AVs because they perceive them as too risky to use. The two contradicting facts—expected decreasing accident rates and high consumer risk perception—highlight the importance of linking user perception of the technology with trust and risk perception. Research on the characteristics of technology is now widespread and is based mainly on TAM and, less often, on UTAUT. However, while both of these models focus on user perceptions of technology use, neither model includes two factors that are of paramount importance in the use of AVs: perceived risk and trust. In our opinion, the discrepancy between the intention to use and the perception of the real benefits of the technology lies in these two factors. In our research, we integrate the effects of these two factors into the UTAUT model and examine how they influence future intention to use.

This study makes the following contributions. First, it examines the UTAUT model in a consistent way in the frame of AV acceptance. Second, it is one of the first studies to empirically test how potential users' trust mediates the relationship between the variables of the UTAUT model and future intention to use AVs. By doing so, this study answers the call from Siegrist [60], who highlighted the importance of examining the construct of trust in artificial intelligence (AI) related technologies. Third, this study adds perceived risk as a mediator, and claims that the role of increased trust is to reduce the perceived risk associated with AVs that may enhance adoption. We point out that perceived performance, effortless use, support, and social influence should enhance trust and, only if trust is built, can the perceived risk be reduced. This finding holds important implications not only for theory but also for practice.

This paper is organised as follows. An in-depth literature review explores the UTAUT model in the AV context with the integration of trust and perceived risk. Based on the literature review, we propose and test a theoretical model of AV acceptance with the help of structural equation modelling (SEM). Next, we present the context and the research method, followed by a summary of the empirical results. Finally, we present the evaluation of these results.

2 Literature review

The role of technology adoption models is key to testing the adoption of different new technologies [24]. Davis [20] created the most popular model, TAM. Venkatesh et al. [65] further advanced this model in the *UTAUT* model. The UTAUT model incorporated eight different theories with four main variables: performance expectancy, effort expectancy, social influence, and facilitating condition. For AV technologies, the majority of studies have used TAM [17, 40, 73], 2020), while testing of the UTAUT model is less common [9, 31, 43, 44]. The UTAUT model has been applied in many areas to explore the factors that may influence attitudes towards, intention to use, or adoption of a new technologies. However, since the 2010s, an increasing number of researchers have pointed out that the four UTAUT variables alone are not sufficient,the adoption of technologies requires the trust of users and that they do not feel using the technology is a risk. As a result, perceived risk and trust appear in several studies, both separately and together, as important complementary factors of the UTAUT model. In the following section, we present the possible variants of the UTAUT model with perceived risk and trust variables. As there is relatively little research on this topic in the AV context, we first summarise research that has examined these effects in other industries.

2.1 Trust and/or risk as antecedent factors to the UTAUT model

In addition to the UTAUT variables, researchers have investigated the role of perceived risk and trust as key factors influencing the intention to use technology. This approach reflects the view that trust and risk do not depend on and have no relationship to the perceived factors of technology, and therefore affect behavioural intention (BI) independently of them.

The inclusion of perceived risk in UTAUT models indicates that higher perceived risk leads to lower BI. Martins et al. [46] confirmed this, showing that increased risk decreases adoption rates. Studies in various industries, such as online banking [30] and mobile banking [64], support this finding. The need for enhanced security in these contexts is critical for increasing adoption. Trust, on the contrary, positively impacts BI, as demonstrated by multiple studies. Oh and Yoon [50] found that trust in online information services enhances adoption by ensuring the technology's security and stability. Alaiad and Zhou [2] argued that reducing doubts through reliable and efficient technology increases trust and adoption. Putri [55] emphasised that minimising system failures can enhance trust.

As a complement to the UTAUT variables, the joint inclusion of perceived risk and perceived trust as relevant predictors of BI has been investigated in some studies, but their relationship to each other and the UTAUT variables is not obvious. Namahoot and Jantasri [49] found that reducing risk increases the intention to use cashless payment systems, and higher trust directly increases BI. Slade et al. [61] showed that increased trust reduces perceived risk, which in turn raises the intention to use remote mobile payments.

While most research has treated the role of risk and trust as merely complementary factors in the UTAUT model, other researchers pointed out that the UTAUT and the risk/trust variables are not independent of each other. However, the link is not clear. Recent studies have integrated perceived risk and trust as mediating factors between UTAUT variables and BI. Sharma et al. [59] demonstrated that trust influences technology adoption through all UTAUT variables in autonomous shopping systems. However, Chang et al. [13] noted that perceived risk did not mediate the relationship between effort expectancy and performance expectancy in online shopping. Interestingly Martins et al. [46] proposed a mediation only in the case of effort expectancy and usage behaviour and not for the other three UTAUT variables.

In summary, the interplay between trust, risk, and the UTAUT variables is complex. While trust and risk independently impact BI, they also mediate the effects of UTAUT variables on technology adoption.

2.2 UTAUT and perceived risk/trust in the context of AVs

The UTAUT model has also been widely used in research on AVs, although not as often as TAM. For the four basic UTAUT variables, performance expectancy and effort expectancy have been primarily included [9, 31, 56], social influence is researched less frequently [43], and facilitating conditions almost never [44]. There are very few studies that systematically examine the impact of all four core variables on BI [25, 27, 44], mostly highlighting only one of its elements and examining the impact on that element. The results suggest that, with some exceptions, the four core variables have a positive impact on BI.

While risk and trust factors have been examined as a complement to the UTAUT model in other industries, as already described herein, this is still in its relative infancy in the case of AVs. This result is somewhat surprising because, as emphasised in the introduction, the role of trust and risk in AVs is generally considered to be of central importance. Those studies that have already addressed the factors of trust and risk when testing the UTAUT model have primarily captured them as an additional factor. They simply treated the variables as additions to the four basic variables within the model [14, 28, 47, 53]. Kapser and Abdelrahman [28] investigated the impact of perceived risk and concluded that we can increase the acceptability of AVs by reducing risk perception. Chen et al. [14] also added perceived risk to the UTAUT model in their research on public acceptance of driverless buses. The new variable significantly affected BI and had a stronger effect than the four UTAUT variables. It can be concluded, therefore, that the lower the risk perception of individuals, the more likely they are to adopt the technology.

Trust is a more frequently studied variable. Gaining the trust of users and creating a sense of security is most needed to increase adoption, rather than improving the technology, which Korkmaz Aslan et al. [37] demonstrated with the positive effect of the variable trust. Meyer-Waarden and Cloarec [47] included the technology trust variable in the UTAUT model. Their research highlighted that perfect technology and data security are needed to increase adoption, and the existence of security is more important to them than the level of automation. However, Pande and Taeihagh [53] incorporated trust in governance as an additional variable in the UTAUT model instead of trust in technology and demonstrated its positive impact, which highlighted the important role of government.

Studies are less frequent in the field of AVs where the UTAUT model has been extended to include both trust and risk, either as direct effect variables [11, 37, 74] or as interacting factors [29, 57]. Risk or its subcomponents do not always show a direct relationship with BI [37]. [11] demonstrated that performance risk has a negative effect on adoption, but the effect of privacy risk is insignificant. This suggests that government and developers should emphasise security in their campaigns. Within perceived risk, Zheng and Gao [74] found technical and psychological risks to have the most negative impact on willingness to use.

Chan and Lee [12], by demonstrating the direct positive effect of trust, pointed out the need to make information about the safety of AV technology easily accessible to increase adoption. However, Kapser et al. [29] investigated not only a direct but also an indirect effect of the trust in technology variable. They showed that perceived risk mediates the positive effect of perceived trust on BI, i.e., trust negatively affects perceived risk, a result first demonstrated in an autonomous delivery vehicle (ADV) context.

Of the UTAUT variables, the impact of social influence was most often examined through the trust or perceived risk variables. Chan and Lee [12] demonstrated the mediating role of trust between social influence and BI. They suggested that if people built trust in AV technology through trusted information, it could increase public acceptance of AV technology. Yuen et al. [71] also examined the impact of UTAUT variables indirectly, through the mediating role of perceived value and trust. Their findings suggested that for autonomous public transport, all variables in the UTAUT model affect perceived value. This influences adoption both directly and through trust as a mediating variable, i.e., decision-makers should place more emphasis on user's value perception and increase trust by purchasing from reliable and predictable AV manufacturers.

3 Research model and hypotheses

Next, we present our hypotheses on which we formulated our research model. We first introduce the hypotheses on the direct relationships between variables of the UTAUT model and future use behaviour of AVs. In the second set of hypotheses, we present the indirect relationship with the mediation of trust and perceived risk as the two focal variables of our research concept.

3.1 Performance expectancy

[65] p. 447 introduced the performance expectancy concept as "the degree to which an individual believes that the system helps to improve job performance". This was later modified so that performance expectancy is a measure of belief in the benefit of using AVs [66]. The use of this construct has a strong predictive role in the adoption of AVs [17, 28, 40]. Performance expectancy has also impacted the behavioural intention to use ADVs, by increasing flexibility, convenience, transparency, and consumer orientation [29], p.2021). In Chen et al.'s [14] formulation, performance expectancy refers to the public's subjective feelings of satisfaction with their travel needs, and the extent to which it increases work efficiency or improves quality of life. These factors increase the adoption of driverless buses. In research by Ribeiro et al. [57], performance expectancy is a measure of belief in the increase in satisfaction with the tourism experience when using AVs. The performance of AVs is expected to be better compared to conventional vehicles [51], which increases the productivity, convenience, and mobility of travellers for those with limited transport options [22]. It may also increase the performance of travellers through productivity gained from leisure time [5, 39]. Based on these research results, we propose a direct relationship between the performance expectancy of an AV and its future usage intention.

H1 Performance expectancy of an AV has a positive effect on intention to use AVs in the future.

3.2 Effort expectancy

Effort expectancy is defined as "the degree of ease associated with the use of the system" [66], p.159). Yuen et al. [71] interpreted effort expectancy as the ease of use of autonomous transport option. Effort expectancy is also an important predictor of the adoption of AVs [17, 70]. It is low when using AVs [11], and therefore provides a good mobility option for those with limited mobility [8, 22]. However, Zhang et al. [73] drew attention to the need for learning before use, which can reduce effort expectancy. However, for ADVs, extra effort does not clearly strengthen the intention to use [28]. Chen et al. [14] identified effort expectancy with the ease of use or the degree of effort, i.e., if the technology is accessible and easy to use, then adoption will be more positive.

H2 The less effort required to use an AV, the stronger the intention to use it in the future.

3.3 Social influence

[65] p. 451 defined social influence as "the degree to which an individual perceives that significant others believe he or she should use the new system". Based on Yuen et al. [71], social influence is a measure of the extent to which society is perceived as a reference point in autonomous public transport use,this is nearly identical to the perceived social norms variable from the Theory of Planned Behaviour model. Social influence has been identified less often as an important predictor of the adoption of Avs. In this context, social influence can be conceptualised as "how an individual perceives the importance of others' opinions in engaging autonomous vehicle technology" [12], p.54). Chen et al. [14] demonstrated the direct influence of surrounding social groups on individual adoption in the case of driverless public transport. Chan and Lee [12] investigated the influence of peers, family, and media, while Panagiotopoulos and Dimitrakopoulos [52] tested only the increasing influence of family and friends on the adoption of Connected-Automated Vehicle technology. In an intercultural study, Kaye et al. [32] found that while social influence in Australia and France was a significant predictor of AV acceptance, in Sweden it had no explanatory power.

Compared to performance and effortless use of AVs, relatively little research has integrated the concept of social influence into AV adoption models. We believe, however, that what the rest of society thinks about its use will be an important part of the future adoption process.

H3 Social influence has a positive effect on intention to use AVs in the future.

3.4 Facilitating condition

[65] p. 453 defined a facilitating condition as "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system". By 2012, this had been modified as "consumers' perceptions of the resources and support available to perform a behaviour" [66], p.159). For ADVs, the more facilitating factors consumers are aware of, the more willing they are to use the technology [28]. Park et al. [54]

reinforced the positive effect of facilitating conditions, while Kaye et al. [32] did not find any significant effect.

Even though relatively little research has integrated the concept of facilitating conditions into AV adoption models, we propose that an important part of the future adoption process will be to ensure that support is in place for the use of AVs. In our research, we focus on the support part of this factor and propose that the more support the potential AV users perceive, the more willing they will be to accept it.

H4 Facilitating conditions have a positive effect on intention to use AVs in the future.

3.5 The role of trust and risk as a mediator

The first part of our hypotheses was related to how the dimensions of technology perception directly contribute to adoption. Though not in such a consistent manner, each of these relationships has been reported separately in studies. What is much less researched, however, is that these variables not only directly increase future use but also indirectly with the mediation of trust and perceived risk.

Trust is of particular importance for the adoption of AVs [12, 17, 31, 70]. It is useless for AV manufacturers to produce what they perceive to be high-performance, high-quality vehicles if potential users do not trust that they will receive a safe transport alternative that is reliable and accident-free,whatever benefits they perceive (whether performance or ease of use), they will not use it [72]. As we summarised in Sect. 2.2., trust does not serve as a focal construct in the UTAUT models in AV acceptance literature. While a considerable body of research has shown that trust and perceived risk have a significant effect on AV acceptance [17, 33, 41, 45, 73, 7], it has not yet been included in the UTAUT model as a mediator between technology perception and future use intention. Contrary to these studies, we think that trust and perceived risk have a central role in AV acceptance. We suppose that the positive perception of the UTAUT variables should first increase trust in technology that will lead to a reduced perceived risk, and then lower risk perception is expected to increase future use.

Based on this argument we suppose that in the context of AVs, consumers will more likely trust such systems if they perceive them as an efficient way to travel, need effortless use, are socially accepted, and have adequate support behind them.

H5 Performance expectancy of an AV has a positive effect on trust in AV performance.

H6 Effort expectancy of an AV has a positive effect on trust in AV performance.

H7 Social influence has a positive effect on trust in AV performance.

H8 Facilitating conditions have a positive effect on trust in AV performance.

One of the most significant barriers to the future use of AVs is the perception of risk by potential users. Several studies have shown that reducing risk is a significant contributor to final adoption [28, 40, 68, 73]. One of the most important ways to reduce risk perception is to increase trust in the safety of the operation [16]. Our hypothesis is therefore that increased trust based on the perceived positives of technology reduces perceptions of operational risk, which ultimately increases adoption. Our hypotheses are as follows:

H9 Trust in AV performance reduces perceived risk of using an AV.

H10 Perceived risk of using an AV has a negative effect on the intention to use AVs in the future.

Our theoretical model based on the hypotheses is illustrated in Fig. 1.

4 Measurement and research design

Our research was based on an online questionnaire. The literature distinguishes between five levels of automation by the Society of Automotive Engineers [58]. We focused on SAE level 5, when we talk about full automation, i.e., everything is done by the vehicle. Based on the hypotheses, we defined seven variables that we included in our measurement model. To ensure the validity of the scales, we used existing scales from the literature. The source and itemised list of scales can be found in Table 1. Of the seven factors included in the final analysis, one was an outcome variable measuring willingness to use. The factors were primarily based on elements of the UTAUT model and the perceived risk and trust literature, focusing on research mainly on self-driving cars or similar digital technologies. We used Waung et al.'s [68] definition for trust in AV performance (with three statements), defined as the vehicle's ability to operate in a safe and efficient manner. Perceived performance risk (with four statements) for AVs refers to the concern about the safety due to system, performance, or equipment failure [73]. For measuring the UTAUT variables, we based our measures on the original Venkatesh et al.

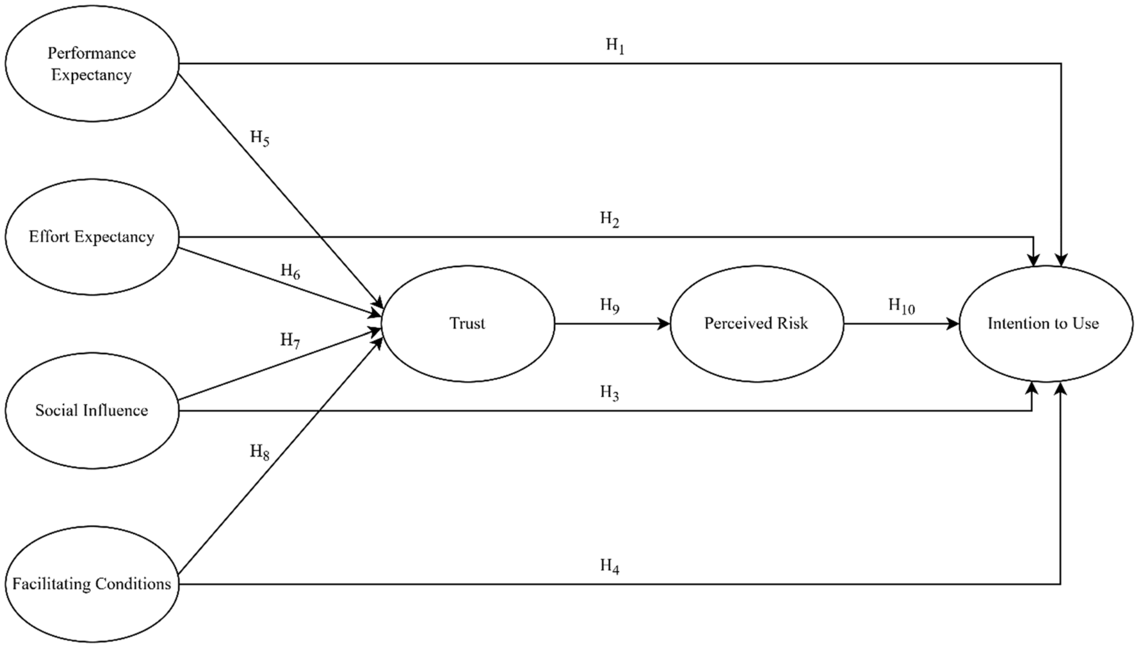

Fig. 1 Research model and hypotheses

Table 1 Items and source of measurement scales

Constructs	Items	Description of the attributes	Source
Perceived Risk (Risk)	Risk1	Chances are high that something will go wrong when using autonomous vehicles	Based on Zhang et al. [73]
	Risk2	Autonomous vehicles may not perform well, and problems may occur when using them	
	Risk3	Considering the potential future service performance of autonomous vehicles, their use could be risky for me	
	Risk4	I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents	
Trust (Trust)	Trust1	I can trust that driverless cars can provide a robust and safe mode of transport	Based on Waung et al. [68]
	Trust2	Driverless cars can be trusted to carry out journeys effectively	
	Trust3	I trust driverless cars to keep my best interests in mind	
Performance Expectancy (PerfExp)	PerfExp1	Using driverless vehicles could improve my living and working efficiency	Based on Venkatesh et al. [66]
	PerfExp2	Using driverless vehicles could increase my living and working productivity	
	PerfExp3	I find that driverless vehicles are useful	
Effort Expectancy (EffortExp)	EffortExp1	Learning how to operate the system would be easy for me	Based on Venkatesh et al. [66]
	EffortExp2	I would find the system easy to use	
	EffortExp3	It would be easy for me to become skillful at using the system	
Social Influence (SI)	SI1	People who influence my behaviour think that I should use the system	Based on Venkatesh et al. [66]
	SI2	Most of my friends would use the system	
	SI3	People who are important to me think that I should use the system	
Facilitating Condition (FC)	FC1	A specific support system would be available inside the car	Based on Venkatesh et al. [66]
	FC2	A specific person would be available for assistance with the car	
	FC3	A specific person would be available who helps in using the car	
Intention to use (ItoUse)	IU1	I predict I would use autonomous vehicles in the future	Based on Zhang et al. [73]
	ItoUse2	I plan to use autonomous vehicles in the future	
	ItoUse3	I will purchase an autonomous vehicle as my next car	
	ItoUse4	If the opportunity arises, I will use a self-driving car in the future	

[66] scales. Performance expectancy (with three statements) is a measure of belief in the benefit of using Avs [66]. The effort expectancy factor (with three statements) is the expected ease of use of the AV system [66]. Social influence measures the extent to which an individual perceives how people who are important to them think they should feel about using the AV system [66]. A facilitating condition is the consumers' perception of the resources and support available to implement AV use [66]. Finally, intention to use measures the willingness of individuals to try and use AVs in the future [73]. The questions asked respondents to rate on a Likert scale from 1 to 7, with (1) *strongly disagree* and (7) *strongly agree* with the given statement. In the survey, we aimed to maintain attention and increase the likelihood of conscious completion, therefore we used a total of four statements in a hidden way. Only respondents who answered these questions correctly were included in the final analysis.

We conducted the research online (CAWI) through Qualtrics in Hungary with Hungarian respondents. Respondents were reached by random and snowball sampling. After the screening process we had 938 usable questionnaires. The average age of the respondents was 30.5 years, the standard deviation was 16.5 years, and the median was 21 years; 61.1% of respondents were female, while 38.9% were male. Residents of the capital were in the same proportion as residents of smaller cities (33%), while 16% of the respondents lived in larger cities. Of the total sample, 65.4% had a secondary school diploma, and 30% had a higher degree diploma. We did not set up the need for a driver's licence as a filtering issue, as SAE level 5 cars will no longer require driving skills.

5 Results

We constructed a model based on covariance-based structural equation modelling (CB-SEM) with the factors already presented. To sort the items into factors, we first performed exploratory factor analysis (EFA) using the maximum likelihood method with Promax rotation. Then, we performed a confirmatory factor analysis (CFA) on the resulting factors. After testing the measurement model with the help of CFA, we tested our hypotheses with the analysis of the structural equations (SEM) using IBM SPSS 25 and IBM SPSS AMOS Graphics licenced software.

5.1 The measurement model

To test if the measurement model was adequate, we performed a CFA analysis. Based on the fitness statistics, we examined the chi-square value ratio by the degree of freedom; in our case, this remained below the critical value of 3 [23], showing a reasonable fit in terms of the difference between the observed and hypothesised covariance matrices. A CFI value above 0.9 for the comparative fit index also makes our model acceptable, as the difference between the hypothetical model and the data is minimal. The root mean squared error of approximation (RMSEA) is also below the 0.08 threshold, which means that the data fit the model well [19]. The standardised root mean square residual (SRMR) also remained below the optimal value of 0.08, so the difference between the observed correlation matrix and the correlation matrix implied by the model is minimal. All of our critical values are appropriate (Table 2).

Our model works well according to the fit indices. We also checked the descriptive statistics and normality of the indicators (Table 3). In terms of factor loadings, minimum values are usually set at 0.5 [4]. Table 4 summarises the results of this analysis. While the average variance extracted (AVE) reaches 0.5, i.e., the convergence validity criterion is also met and the correlation between any two factors is less than the square root of the AVE value, so the discriminant validity also applies. Composite reliability (CR) is greater than 0.7, making the scales reliable [23]. Table 5 summarises the results of the discriminant validity test and all values meet the criteria.

5.2 Structural model assessment

Finally, we tested the direct and indirect effects of the model (Tables 6 and 7). The explanatory power of the model is very strong; the R^2 values are higher than 0.5. We were able to accept all hypotheses except those that measured the effect of social influence. As social influence had no significant effect on intention to use and on trust, we rejected both H_3 and H_7. Performance expectancy has a significant positive direct effect on intention to use ($\beta = 0.571$, $p < 0.001$), and has the strongest effect in the whole model on trust ($\beta = 0.883$, $p < 0.001$), so we accepted both the H_1 and H_5. Effort expectancy

Table 2 The fit indices and results of the CFA and the final SEM Model

Fit index	Recommended Thresholds	CFA Construct	SEM Model
χ^2/df	< 3	2.458	2.802
CFI	> 0.90	0.987	0.984
RMSEA	< 0.08	0.052	0.057
SRMR	< 0.08	0.033	0.038

χ2/df = Chi-square divided by the degrees of freedom; CFI = Comparative Fit Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardised Root Mean Square Residual

Table 3 Descriptive statistics and normality tests of the constructs in the model

Construct	Indicators	Minimum	Maximum	Mean	SD	Corrected Item-Total Correlation	Skewness	Kurtosis
Performance Expectancy	PerfExp1	1	7	4.47	1.480	0.838	−0.331	−0.454
	PerfExp2	1	7	4.36	1.547	0.841	−0.274	−0.647
	PerfExp3	1	7	4.68	1.494	0.699	−0.395	−0.270
Effort Expectancy	EffortExp1	1	7	5.06	1.393	0.906	−0.759	0.267
	EffortExp2	1	7	5.04	1.385	0.933	−0.830	0.419
	EffortExp3	1	7	5.11	1.373	0.913	−0.897	0.607
Social Influence	SI1	1	7	4.11	1.638	0.799	−0.249	−0.778
	SI2	1	7	4.34	1.641	0.829	−0.379	−0.656
	SI3	1	7	4.48	1.556	0.841	−0.575	−0.374
Facilitating Condition	FC1	1	7	4.39	1.659	0.871	−0.455	−0.586
	FC2	1	7	4.58	1.685	0.927	−0.609	−0.551
	FC3	1	7	4.75	1.682	0.909	−0.747	−0.360
Trust	Trust1	1	7	4.41	1.356	0.732	−0.481	0.032
	Trust2	1	7	4.83	1.279	0.769	−0.643	0.394
	Trust3	1	7	5.04	1.320	0.713	−0.855	0.800
Perceived Risk	Risk1	1	7	4.34	1.382	0.770	−0.105	−0.523
	Risk2	1	7	4.68	1.316	0.728	−0.354	−0.364
	Risk3	1	7	4.10	1.455	0.721	−0.019	−0.706
	Risk4	1	7	5.04	1.532	0.647	−0.585	−0.393
Intention to Use	ItoUse1	1	7	4.23	1.679	0.881	−0.272	−0.800
	ItoUse2	1	7	4.05	1.759	0.905	−0.101	−1.019
	ItoUse3	1	7	3.71	1.719	0.852	0.117	−0.910
	ItoUse4	1	7	4.31	1.728	0.900	−0.386	−0.846

ItoUse = Intention to use; PerfExp = Performance Expectancy; EffortExp = Effort Expectancy; SI = Social Influence; FC = Facilitating Condition; Trust = Trust; Risk = Perceived Risk; SD = Standard Deviation

also has a significant positive effect on intention to use ($\beta = 0.095$, $p < 0.001$) and on trust ($\beta = 0.043$, $p < 0.001$), which means that we can accept both H_2 and H_6. In addition, facilitating conditions have a significant positive effect on intention to use ($\beta = 0.257$, $p < 0.001$) and on trust ($\beta = 0.187$, $p < 0.001$), so in this case we can accept H_4 and H_8. As trust has a strong significant negative impact on perceived risk ($\beta = -0.779$, $p < 0.001$), we also accepted H_9. Finally, we can accept H_{10}, because perceived risk has a significant negative effect on intention to use ($\beta = -0.098$, $p < 0.001$). We checked one control variable (driving licence ownership) in the SEM analysis. It had no significant effects on each dependent variable.

In most cases, a partial mediating effects were found. Of the four UTAUT variables, performance expectancy ($\beta = 0.089$, $p < 0.01$), facilitating condition ($\beta = 0.007$, $p < 0.05$), and effort expectancy ($\beta = 0.018$, $p < 0.05$) have an indirect effect through trust and perceived risk on intention to use. These paths are partially mediated through the two mediators (trust and perceived risk). Only for social influence is there no indirect or direct effect at all (Fig. 2).

6 Discussion

TAMs contribute to understanding the determinants of AV adoption, yet they lack user-specific variables that influence final adoption. In our research, we integrated two such variables into a newer version of acceptance models, namely the UTAUT model. The factors of trust and perceived risk are central variables that play an important role in whether the perceived characteristics of the technology lead to adoption.

In our research, we tested how the variables in the UTAUT model directly and indirectly affect adoption and demonstrated that trust and perceived risk are indeed important mediators between technology characteristics and adoption. The UTAUT model is the newest and most complete among the models of technology acceptance, as it combines the essence of the models tested and accepted so far. While the model has been tested for other technological innovations [3, 27, 28], AV research has rarely tested the model as a whole [21], with only parts of it having been published [12, 29, 47]. In this paper, we examine all four main factors of the UTAUT model in terms of both direct and indirect effects.

Table 4 Results of the confirmatory factor analysis

Construct	Indicators	Indicator loadings	Average Variance Extracted (AVE)	Composite Reliability (CR)	Cronbach α
Performance Expectancy	PerfExp1	0.816	0.670	0.859	0.893
	PerfExp2	0.806			
	PerfExp3	0.833			
Effort Expectancy	EffortExp1	0.929	0.893	0.961	0.961
	EffortExp2	0.965			
	EffortExp3	0.940			
Social Influence	SI1	0.845	0.776	0.912	0.912
	SI2	0.883			
	SI3	0.914			
Facilitating Condition	FC1	0.917	0.886	0.959	0.954
	FC2	0.948			
	FC3	0.959			
Trust	Trust1	0.851	0.697	0.873	0.862
	Trust2	0.806			
	Trust3	0.847			
Perceived Risk	Risk1	0.796	0.596	0.855	0.864
	Risk2	0.727			
	Risk3	0.835			
	Risk4	0.724			
Intention to Use	ItoUse1	0.926	0.827	0.950	0.953
	ItoUse2	0.939			
	ItoUse3	0.857			
	ItoUse4	0.914			

ItoUse = Intention to use; PerfExp = Performance Expectancy; EffortExp = Effort Expectancy; SI = Social Influence; FC = Facilitating Condition; Trust = Trust; Risk = Perceived Risk

Table 5 Discriminant validity of the constructs

	Correlations and square roots of AVEs						
	ItoUse	**PerfExp**	**EffortExp**	**SI**	**FC**	**Trust**	**Risk**
ItoUse	**0.910**						
PerfExp	0.811	**0.818**					
EffortExp	0.496	0.449	**0.945**				
SI	0.690	0.653	0.318	**0.881**			
FC	0.736	0.627	0.382	0.766	**0.942**		
Trust	0.831	0.817	0.480	0.639	0.679	**0.835**	
Risk	−0.644	−0.577	−0.367	−0.515	−0.549	−0.725	**0.772**

Bolded items in diagonal are Square Roots of AVEs and the other items are the correlations. ItoUse = Intention to use; PerfExp = Performance Expectancy; EffortExp = Effort Expectancy; SI = Social Influence; FC = Facilitating Condition; Trust = Trust; Risk = Perceived Risk; AVE = Average Variance Extracted

In terms of direct effects, the two most frequently examined factors, performance expectancy and effort expectancy, in line with the literature have significant positive effects in our study. This implies that if potential users perceive the positive impact of AVs on increasing their efficiency, and thus feel that their lives are made easier and simpler, they will be more willing to use these vehicles. This finding suggests that customers are more inclined to trust AVs that are seen to be more user-friendly. Likewise, if they think that using AVs will be easy and that they will not have problems with the complexity of the technology, this will also help to increase acceptance. Users will have complete trust if the system is seen as fast, reliable, and easily accessible whenever they need to use it. Although the effect of both variables is significant, the magnitude of their effect is different. The

Table 6 Structural model estimates

	Direct effect (standardized estimates)	Direct effect (unstandardized estimates)	S.E	C.R
EffortExp → Trust	0.043***	0.037***	0.008	4.771
PerfExp → Trust	0.883***	0.865***	0.012	73.697
SI → Trust	− 0.027$^{(ns)))}$	− 0.024 $^{(ns)))}$	0.016	− 1.485
FC → Trust	0.187***	0.137***	0.010	13.958
Trust → Risk	− 0.779***	− 0.722***	0.019	− 38.320
EffortExp → ItoUse	0.095***	0.114***	0.019	6.144
PerfExp → ItoUse	0.571***	0.774***	0.033	23.107
SI → ItoUse	0.028$^{(ns)))}$	0.032$^{(ns)))}$	0.027	1.168
FC → ItoUse	0.257***	0.261***	0.023	11.136
Risk → ItoUse	− 0.098***	− 0.145***	0.030	− 4.860
Control variables				
License (dummy) → Trust	− 0.004$^{(ns)}$	− 0.011$^{(ns)}$	0.021	− 0.524
License (dummy) → Risk	0.028$^{(ns)}$	0.067$^{(ns)}$	0.050	1.345
License (dummy) → ItoUse	0.018$^{(ns)}$	0.064$^{(ns)}$	0.049	1.310

Bootstrapping based on n = 2000 subsamples. *** $p < 0{,}001$; ns = non significant; License reference '0' is 'Owning a B2 driving license'

R^2(Trust) = 0.946; R^2(Risk) = 0.617; R^2(Intention to use) = 0.841

R^2 = Squared Multiple Correlations; S.E. = Standardized Error; C.R. = Critical Ratio; ItoUse = Intention to use; PerfExp = Performance expectancy; EffortExp = Effort expectancy; SI = Social influence; FC = Facilitating condition, Trust = Trust; Risk = Perceived risk; License = Respondent driving license ownership

Table 7 Indirect effect and estimates

	Indirect effect (unstandardized estimates)	Lower	Upper	Results
PerfExp → Trust → Risk → ItoUse	0.089***	0.049	0.132	Partial mediation
EffortExp → Trust → Risk → ItoUse	0.007***	0.001	0.018	Partial mediation
SI → Trust → Risk → ItoUse	− 0.004$^{(ns)))}$	− 0.013	0.003	No mediation
FC → Trust → Risk → ItoUse	0.018***	0.008	0.033	Partial mediation

Bootstrapping based on n = 2000 subsamples. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ns = non-significant; ItoUse = Intention to use; PerfExp = Performance Expectancy; EffortExp = Effort Expectancy; SI = Social Influence; FC = Facilitating Condition; Trust = Trust; Risk = Perceived Risk

effect of effort expectancy (β = 0.11) is relatively small, especially when compared to the effect of performance expectancy (β = 0.48). This result has been reported in several AV-related studies, and in some studies the effect of effort expectancy is not even significant [28, 34, 56].

There are several possible explanations for this. If we look at the average perception of the two variables, we can say that the mean of the expectation of performance (M = 4.5) is significantly lower ($p < 0.01$) than the prior perception of effortless use (M = 5.07). This indicates that potential users are more afraid that the technology will not help their daily life than they are of not being able to use it. Accordingly, the impact on adoption is also more significant, i.e., those who feel that AVs are really useful are more likely to adopt them. The perceived complexity of using the technology is less present in users' perceptions, probably because one of the perceived benefits of AVs is their accessibility and usability by anyone, unlike traditional vehicles.

While performance expectancy and effort expectancy are relatively more commonly studied factors in AV research, the effects of social influence and facilitating conditions have been much less studied and have also given conflicting results. Our research results show that social influence has no effect on adoption. This may suggest that at this stage of AV development, the decisive factor is not yet what important others think about using the technology, as it is not yet a real option. In our view, the impact of social influence will be amplified when the technology becomes available to all, and the opinions of others become important in making a concrete choice.

In our research, we measured facilitating conditions slightly differently from the original operationalisation. For AVs, it is still difficult to estimate exactly how much a car will cost, so it is difficult for the respondents to estimate whether they will have the necessary financial resources. It is also difficult to estimate in advance, even at the perceptual level, how much knowledge they need

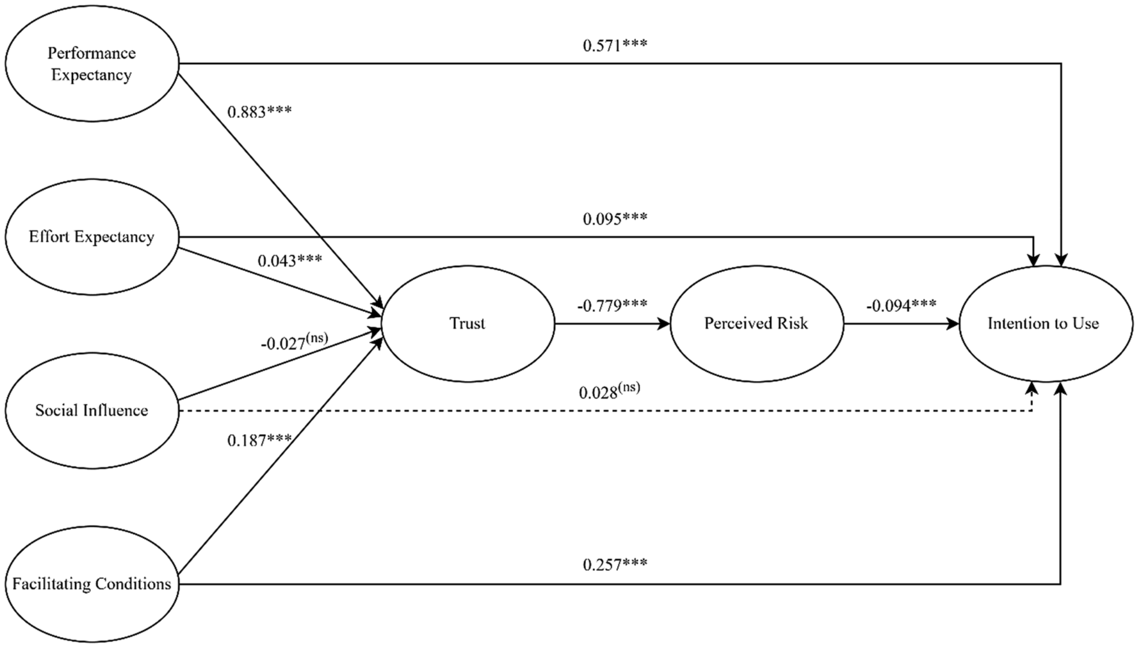

Fig. 2 Results of the structural model. *Note* Dotted lines indicate non-significant relationships

to use it. What can be very important for future users is adequate support. In our research, we relied primarily on this dimension. Our results show that support is very relevant to adoption: facilitating conditions is the second most important determinant of AV adoption. This result has important theoretical and practical (to be discussed later) implications. From a theoretical point of view, the support role has not received significant attention in the AV adoption literature. Thus, the results of our research may contribute to highlighting the role of support and may initiate future research on the topic.

The most important contribution of this study, besides the systematic analysis of UTAUT factors, is the inclusion of trust and perceived risk in the model. Relatively few research studies are available in this area, so there may be important theoretical implications for our results. Our starting hypothesis is that trust and perceived risk are not only among the many factors influencing adoption but they also play a central role. Our results confirm this assumption. Trust partially mediates the effects of performance expectancy, effort expectancy, and facilitating conditions. These factors not only directly affect adoption, but also indirectly by first influencing trust in AVs, which reduces the perceived risk of use and thus leads to adoption. Trust has a significant impact on perceived risk and can influence adoption through its reduction.

The magnitude of the effects of the UTAUT factors on trust are somewhat similar to the direct effects. Performance expectancy has the strongest impact on trust in AVs, followed by facilitating conditions, and finally effort expectancy, with a much weaker effect. Social influence is not significant; thus, the effect of important others is not only directly but also indirectly not significant for adoption. This suggests that at the current stage of development, perceptions of efficiency and support have the greatest impact on trust.

We included one control variable in our model, a driving licence, i.e. the user can drive. Interestingly, having a driving licence has no effect. This result may suggest that it is not necessarily having a licence that may influence adoption, but rather experience. Chen et al. [15] support this. They found that how long someone has been driving is a much stronger influencer than having a licence, leading them to conclude that driving experience may be more of an influencing factor. We agree with this result, suggesting that the trial of AVs will depend less on the possession of a driving licence and more on the building blocks of trust.

6.1 Managerial implications

Our research has not only theoretical but also practical implications. First, among the basic variables of the UTAUT model, expected performance, effortless use, and positive perceptions of an appropriate supportive environment can increase trust and facilitate the adoption of potential users. In practice, this means that it is worth paying attention to the design of these factors. The most important influencing factor for the user is the effective use of AVs in everyday life. If both in terms of design and communication, manufacturers can develop the perception that AVs will make people's lives significantly easier and offer real advantages over conventional vehicles, then it is likely that many more people will think of them as a viable alternative. Since time is an important factor in people's lives, it may be worth stressing time saving as an efficiency criterion. It may also increase the perception of efficiency to highlight that driving AVs does not require expensive and time-consuming courses; anyone can drive them. Not only does performance expectancy increase adoption directly, but it also increases it indirectly through the mediation of trust. This finding highlights the importance of increasing the perceived benefits of using AVs. Marketing professionals should communicate this information to customers, as AVs and their use are new and their benefits are not fully understood. Developers need to work with marketing professionals to raise awareness and help customers understand the benefits of AVs.

Related to this, however, is the importance of providing adequate support to users, as this is the second most important factor in adoption. To the extent that people feel that they are getting help to use cars, they will be more willing to use them. Support can be very diverse. The first priority is to provide support that builds confidence and enables the user to contact someone who can help with any problem. This is particularly necessary at the beginning of the lifecycle, until users become experienced in driving an AV. But support can also mean legislation that helps build trust and provides appropriate legal, statutory support for car users. Communicating support is also of crucial importance and can shape user perceptions of the reliability of AV.

Effort expectancy also has an impact on adoption, albeit not a strong one, which indicates to developers that there is a prior expectation among users that this technology will not be complicated. It is important to meet this during development to ensure that people actually adopt AVs.

The central role of trust and perceived risk resolves the contradiction that if AV technology does indeed reduce the risk of accidents, why do people perceive its use as risky? It is important for AV manufacturers and the regulatory environment to address distrust of AVs as a way to reduce risk perception and increase acceptance. Our results show that emphasising performance efficiency and support are key tools for building trust. As these two factors have the strongest impact on trust, communication on improvements, with a particular focus on reliability, is needed. Communicating performance efficiency and reliability helps to reduce the commonly accepted view of riskiness, even though accidents caused by AVs often make the news headlines. It is crucial to highlight in communication that, overall, AVs are much more effective in preventing accidents than traditional vehicles.

6.2 Limitations and future research

Although our research reveals new dimensions in the development and impact of trust and risk perception, there are still some details where further research is needed to clarify the mechanisms of its effect. Our research tested the SAE level 5 of AVs, i.e., full automation. Precise estimation of the UTAUT variables may seem difficult for potential users without actual use, thus a real-life experience could enhance the validity of our model. It may be worthwhile testing the results of our research on a sample of people who have already taken a test drive in an AV.

Sources of trust and risk as central variables can also be an important addition to the model. In this research, we have focused on the UTAUT model, but it is possible that other variables – not related to technology perception – also have a significant impact on trust in AVs.

First, it may be worthwhile to include the user's characteristics, either in terms of their attitude towards technology (e.g., technology anxiety or innovativeness) or their attitude towards driving. One of the limitations of our study is that we used ownership of a driving licence as a control variable. Although the existence of a driving licence did not influence the results in our research, other characteristics related to driving (driving experience, how much the driver likes to drive, and how afraid they are of an accident) may have a stronger influence. These variables may yield interesting results regarding their impact on trust. It may also be interesting to examine the impact of the information users have regarding AVs on trust. Knowledge of AVs may be particularly relevant for trust and risk perception. In our research, support played a major role in building trust and acceptance. In the future, it may be worth investigating exactly what type of support is most likely to help build trust and promote acceptance. Further exploration of the sources of trust is an important challenge for AV developers and researchers.

As we did not place AVs in a specific context, we did not use moderating variables in this research. If context-specific factors are added to the effects in the future, this could clarify the exact mechanisms of the relationships between the variables in the model. The factors influencing trust described herein may not only have a direct effect, but also a moderating effect, especially on the personality traits of the user. By including these variables, it is possible to fine-tune the trust-building factors and engage in targeted communication during market entry for consumers.

Author contributions

Zsófia Kenesei: Conceptualization, Methodology, Writing—Original Draft, Revision; Supervising. László Kökény: Methodology, Investigation, Formal analysis, Writing – Original Draft. Katalin Ásványi: Investigation, Writing—Original Draft. Melinda Jászberényi: Funding acquisition, Supervising. The authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests

The authors declare that they have no competing interests.

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