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Trust and perceived risk: How different manifestations affect the adoption of autonomous vehicles

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ABSTRACT

Although manufacturers and experts consider autonomous vehicles (AVs) as a much safer alternative than traditional human-driven vehicles, the lack of trust and high perceived risk by potential users can be a major obstacle to their acceptance. While both risk and trust have been the focus of interest for AV researchers, studies have often produced contradictory results. This study offers a new perspective to investigate the effect of trust and perceived risk to resolve these ambiguities. We identified three underlying dimensions of trust supplemented by two dimensions of risk and incorporated them into one model. The proposed model offers direct and indirect paths between trust dimensions and AV acceptance with the mediation of the dimensions of perceived risk. Based on a survey of 949 adult respondents, the model was tested with structural equation modeling (SEM). Results revealed that only performance trust affected directly intention to use AVs, while trust in manufacturers influenced intention to use with the mediation of privacy risk. An important result is that trust in institutions that can influence future rules and regulations for the use of AVs has no impact either directly or indirectly on intention to use. The practical implications can assist regulators and manufacturers to increase their efforts to build trust and confidence, thus enhancing the adoption of this technology.

1. Introduction

Penetration of autonomous vehicles (AVs) is one of the most significant and remarkable trends in the transportation industry with future scenarios predicting a shift toward self-driving (Miskolczi et al., 2021). Recent research results, however, show that the adoption of AVs by the public is relatively low (Stilgoe and Cohen, 2021). Although the development of AVs is progressing with significant advances in safety, reports of AV-related accidents are reducing the public's confidence and willingness to accept them. Although it is mainly AV accidents that attract the most media attention, it is important that the public recognizes the benefits of AVs and their positive role in transportation (Litman, 2021). Among these benefits is that AVs can significantly reduce accidents, increase human mobility for those who are not able to drive, lower pollution by increased efficiency, and ease traffic congestions (Krueger et al., 2016; Meyer et al., 2017; Piao et al., 2016).

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Using sensors and artificial intelligence (AI) software, AVs can operate the vehicle without a human driver's attention or control. The Society of Automotive Engineers (SAE, 2018) defines six levels of driving automation ranging from 0 (fully manual) to 5 (fully autonomous). Level 0 indicates no automation at all. Levels 1 and 2 provide some automation but with a human driver monitoring the vehicle. At Levels 3, 4, and 5 the vehicle can perform most driving tasks either with a human override (Level 3) or fully without human attention (Level 5).

Our study focuses on the role of trust and perceived risk in the acceptance of Level 5 AVs. Although most research on the adoption of AVs (Buckley et al., 2018; Man et al., 2020; Xu et al., 2018) uses some kind of technology acceptance model (TAM or UTAUT), many of these authors point out that trust and risk are important additional factors for AVs and, without integrating them, it is difficult to apply any of the acceptance models. Besides factors like perceived usability (PU) and perceived ease of use (PEOU), trust is an important prerequisite for people to accept and intend to use self-driving technology (Meyer-Waarden and Cloarec, 2021; Panagiotopoulos and Dimitrakopoulos, 2018; Zhang et al., 2019; 2020). Trust has not only a direct effect but also an indirect effect on intention to use, both through risk reduction and through enhancing the perceived variables of TAM (Buckley et al., 2018; Liu et al., 2019a; Man et al., 2020; Xu et al., 2018). The role of risk in the adoption of self-drivers is less clear. Although it seems evident that the risk posed by self-drivers strongly reduces intention to use (Kasper and Abdelrahman, 2020; Wang et al., 2020; Zhu et al., 2020), several studies have concluded that perceived risk does not significantly influence the future use of AVs (Choi and Ji, 2015; Liu et al., 2019a). It is also unclear what the causal relationship is between trust and risk perception. Siegrist (2021) draws attention to the need for further research on the relationship between trust and risk, as there is currently insufficient evidence on the direction and strength of the relationship.

Most research in this domain measures the impact of trust in a one-dimensional manner. We suggest a different approach. We propose that trust has multiple facets, and these facets have a differential impact on future use. Although most research concentrates on trust in performance, we argue that trust has three distinct dimensions that are closely linked to manufacturers and the institutional background of AVs. Trust in the technology is obviously important for adoption, but in our view, general trust cannot be established if potential users do not trust the technology provider, i.e., the manufacturing companies, or if they do not trust that policymakers (private or public) will properly regulate the production and operation of AVs. Although this threefold distinction has already appeared in one article (Waung et al., 2021), but it did not measure the impact of the manufacturer trust and only tested the impact of the other two dimensions separately. We consider it important to integrate the effects of these trust factors into one single model rather than examine them individually in separate models. Our research is the first to examine these three distinct dimensions in a unified model, measuring the effects not separately but simultaneously using SEM. In this study, we present research results on the effect of the different dimensions of trust, including trust in performance, trust in manufacturers and developers, and trust in regulatory institutions.

While types of trust are rarely examined separately, dimensions of perceived risk are more frequently distinguished, though with contradictory results. In the case of AVs, three risk dimensions – performance, security, and privacy – are the focus of research. While risk as an overall construct often lacks explanatory power on acceptance (Choi and Ji, 2015; Liu et al., 2019a), when distinguishing the different types, it may serve as an antecedent for AV acceptance (Man et al., 2020; Wuang et al., 2021; Zhang et al., 2019). Again, the effect of different risk dimensions on acceptance are rarely integrated and tested in one single model.

The contribution of our research is that it not only studies the parallel effect of the dimensions of trust, but it also integrates into the model the effect of performance and privacy risks as the two most influential risk dimensions concerning AV acceptance. In this way, the results of this research can help explore the relationship between trust and risk dimensions, while also serving as an important starting point for both manufacturers and policymakers in the further development of trust.

The paper is organized as follows. After presenting the literature review, we propose a theoretical model assuming the different dimensions of trust have a direct and an indirect effect on future intention to use AVs with the mediation of the different types of perceived risk. The measurement and structural models are tested with the help of a questionnaire on a sample of 949 respondents. To test our hypotheses, we used structural equation modeling. After presenting the results, we propose theoretical and practical implications and discuss future research avenues.

2. Literature review

2.1. Dimensions of trust

With the spread of automation, trust plays an increasing role in acceptance models of AI led innovations (Ghazizadeh et al., 2012). While there are accepted definitions of trust, there is a limited understanding about the interpretation of trust specifically in the field of AVs (Gold et al., 2015). The most common definition of trust is "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee and See, 2004, p. 51). Kaur and Rampersad (2018) also link dehumanization and the loss of control to trust, so if we trust AVs, it actually means we can give up control of the vehicle. Benleulmi and Blecker (2017) highlight loss of control in relation to the concept of trust, and the sense of vulnerability to the actions of another party in the absence of controllability. Liu et al. (2019a,b) and Xu et al. (2018) support this approach. Man et al. (2020:109847) state "Trust is defined as the extent to which drivers willingly become vulnerable when using an AV," which shows that vulnerability is a key factor in the interpretation of trust. However, others interpret trust not from the perspective of loss of control, but also from the perspective of the existence of functionality. May et al. (2017) argue that trust means the belief that a given system can perform its function. Herrenkind et al. (2019) define trust as the degree of confidence in the predictability and functionality of a given system.

Based on the model of Hoff and Bashir (2015), it is worth distinguishing trust before and during interaction with technologies, as trust can be built on different information at different stages. In the case of AVs, however, it is also important to note that due to the limited opportunities to try the technology, we can only talk about initial trust, as people do not have experience with this technology (Zhang et al., 2019).

Choi and Ji (2015) present different sources of trust, like system transparency, technical competence, and situation management, but conceptualize it with one dimension concentrating on the reliability and trustworthiness of the vehicle. Several researchers accept this conceptualization (Man et al., 2020; Zhang et al., 2019; 2020; Xu et al., 2018) and use the scale developed by Choi and Ji (2015). Contrary to this overall accepted conceptualization, Hengstler et al. (2016) point out that in the case of applied AI, such as AVs, trust is dichotomous in nature. In the case of technologies where knowledge of them is relatively low and initial resistance is high, trust can be built on the perceived predictability of the technology (Hengstler et al., 2016). The source of credibility is not only the technology itself but the trustworthiness of the innovating firm and its communication (Siegrist, 2021). This conceptualization of trust points out that people might reject an innovation even if the technology is trustworthy simply because the organizations behind the technology are not trustworthy (Eiser et al., 2002). Liu et al. (2019a) add an additional aspect to this dimension – trust in government with rules and regulations – and call it "social trust." Waung et al. (2021) go one step further and differentiate not only trust in the vehicle and social trust, but they also divide social trust into two dimensions. While trust in manufacturers and developers refers to the extent to which we trust the organizations that develop and produce the technology, trust in rules and regulations refers to the extent to which we trust the government and other organizations who are responsible for regulating the development and use of technology.

2.2. The role of trust in AV acceptance

The role of trust in the acceptance of AVs has been investigated by several researchers. Some authors examined how trust affects acceptance (Buckley et al., 2018; Choi and Ji, 2015; Kaur and Rampersad, 2018; Liu et al., 2019a). Others demonstrated the link between trust and acceptance through the lack of trust (Abraham et al., 2016; Zmud et al., 2016). There are also studies that examine the effect of trust on different levels of AVs (Gold et al., 2015). Most research demonstrates that the level of trust influences the acceptance of AVs. Shariff et al. (2017) state that if a strong trust in AVs cannot be established, mass acceptance of AVs will not be developed.

Significant parts of research integrate trust into TAM (Davis, 1989; Davis et al., 1989) or the UTAUT model (Venkatesh et al., 2003). The relationship of the two basic variables of TAM, PU and PEOU, with trust and behavior intention (BI) has been studied by several researchers. Panagiotopoulos and Dimitrakopoulos (2018) examined the effects of these variables on adoption independently, of which trust proved to be the second strongest predictor, while Zhang et al. (2020) found that trust served as the strongest predictor. Chen (2019) examined the effect of PU and PEOU in addition to trust but found only an indirect relationship through attitude on BI, while Meyer-Waarden and Cloarec (2021) proved the positive direct effect of trust on BI in addition to performance expectancy and user wellbeing.

Trust is not only an additional variable in TAM and the UTUAT model, but in several cases, it is related to PU and PEOU either as an independent variable or as a mediator. Choi and Ji (2015) found that trust has a positive effect on acceptance through PU. However, others (Dirsehan and Can, 2020; Xu et al., 2018; Zhang et al., 2021) have demonstrated an indirect positive effect on BI for both variables (PU and PEOU). Man et al. (2020) also examined the effect of trust besides PEOU and PU on intention to use, i.e., BI, where PEOU did not affect BI directly but with the mediation of trust. Ribeiro et al. (2021) examined the positive effect of trust on intention to use through perceived performance expectancy.

Contrary to those studies that investigated the effect of trust in a vehicle's performance, Liu et al. (2019a), Liu et al. (2019b) examined the impact of social trust, defined as the trust in the people and institutions behind the technology, and found a positive indirect impact on BI with the mediation of perceived benefits. In two separate models, Waung et al. (2021) measured the effect of performance trust and trust in regulation on intention to use AVs and found significant direct positive effects for both types of trust.

2.3. Different types of perceived risks

Contrary to other areas of automation and the internet environment, where the dimensions of perceived risk are quite often differentiated (Crespo et al., 2019; Wang et al., 2019; Yang et al., 2015), this is not the case for AV acceptance studies. As with trust, most research on perceived risk measures the impact of an overall risk perception construct (Choi and Ji, 2015; Lee et al., 2019; Liu et al., 2019a; Liu et al., 2019b), and relatively little research has gone so far as to distinguish between the different types of risk and measure their impact separately. While some authors differentiate four (Wang et al., 2019) or five (Alshaafee and Iahad, 2019; Benleulmi and Blecker, 2017) types of risk of using AVs, most often two or up to three dimensions are examined, mainly security/privacy risk (Man et al., 2020; Waung et al., 2021; Zhang et al., 2019), safety risk (Man et al., 2020; Zhang et al., 2019), and performance risk (Waung et al., 2021), the latter being closely related to safety risk. Based on Jing et al. (2020), risk may be related to system reliability, data leakage, or security, while Zhang et al. (2021) link it to physical injures, privacy leakage, and financial loss. Kyriakidis et al. (2015) highlighted the perceived risk of AVs in relation to security, legal, and safety aspects. We present the three most commonly used types of risk.

Performance risk is the risk that the AV fails and does not perform as expected (Benleulmi and Blecker, 2017) or barely meets the individual's requirements (Alshaafee and Iahad, 2019). It thus lacks the desired benefits (Wang et al., 2019), which may indicate a weakness associated with a particular service (Lin et al., 2012). Others define this risk as the risk of system reliability, which is steadily declining because of technological advances (Jing et al., 2020). This type of risk is primarily related to technology, querying its safety.

Safety risk refers to the degree of protection of a given system (Alshaafee and Iahad, 2019). It can be defined as the risk of entrusting users' safety to the automated system (Man et al., 2020) and the risk to the safety of the user of the AV, which could also be called security risk (Wang et al., 2019). Hulse et al. (2018) also interpret it as a negative consequence on life. Several authors have identified security risk as the greatest risk (Bansal et al., 2016; Menon et al., 2016). They are most concerned about equipment failure, which causes them to accept AVs less (Zmud et al., 2016). This risk is somewhat related to performance risk, since in the case of an AV, if the car breaks down, it directly endangers the safety of its user by transferring control to the autonomous system.

Privacy or data protection risk refers to the risk of disclosure of data, so it can be defined as a loss of data protection (Benleulmi and Blecker, 2017). It refers to the misuse of personal data (Jing et al., 2020), behavioral data, or travel data (Man et al., 2020). In addition to safety risk, data protection risk is a major concern for users (Bansal et al., 2016; Kyriakidis et al., 2015; Schoettle and Sivak, 2014), mostly concerned with the transmission of travel data or behavioral data that can be used and tracked (Zhang et al., 2019).

2.4. Role of perceived risk in AV acceptance

Several studies demonstrate that perceived risk directly affects acceptance; the lower a person's risk perception, the more they accept AVs (Kapser and Abdelrahma, 2020; Lee et al., 2019; Wang et al., 2019; Zhang et al. 2021, Zhu et al., 2020). Lee et al. (2019) proved that perceived risk reduces intention to use, so people with a low perceived risk of AVs would rather use them. Based on (Kapser and Abdelrahma, 2020), intention to use is negatively affected by perceived risk. Wang et al. (2019) examined the impact of risk on willingness to use and stated that higher risk significantly decreases willingness to use AVs. However, research results are often contradictory in terms of the impact of risk. Some studies that have measured perceived risk found no association between risk and intention to use (Choi and Ji, 2015; Liu et al., 2019a, 2019b).

Besides the studies that measure the effect of perceived risk with a one-dimensional construct, studies that measure the different types of risks are not that numerous and found different results. Zhang et al. (2019) differentiate perceived safety risk and perceived privacy risk with only perceived safety risk proving to have an indirect effect on BI. Man et al. (2020) measured the same types of risk and found similar results. Waung et al. (2021) differentiated perceived AV performance risk and perceived AV privacy/security risk and in both cases found a significant indirect relationship with intention to use AVs. Benleulmi and Blecker (2017) examined the indirect impact of five types of risk. They detected significant impact on BI only in the case of performance and safety risk, but there was no significant relationship between privacy, socio-psychological, and financial risk and BI.

2.5. Relationship between trust and risk

Research models on the relationship between trust in AV and perceived risk by potential users can be divided into two groups according to whether trust or perceived risk is the mediator in their effect on BI.

Studies that treat perceived risk as the independent variable and trust as a mediator (Benleulmi and Blecker, 2017; Man et al., 2020; Waung et al., 2021; Zhang et al., 2019) are based on the implicit assumption that risk perception precedes the development of trust and if users perceive the AV as safe, then they start trusting the technology. Thus, the established trust will lead to the use of AVs. In another interpretation of the relationship between trust and risk, risk is seen as a mediator between trust and acceptance (Choi and Ji, 2015; Liu et al., 2019a, 2019b; Ribeiro et al., 2021; Zhang et al., 2019). The underlying assumption behind this effect is that the initial trust that users hold decreases perceived risk and helps in accepting AVs. In a recent *meta*-analysis, Zhang et al. (2021) constructed two competing models for the relationship between trust, risk, and BI. Based on the results of the *meta*-analytic structural equation modeling, the trust=>risk=>BI with a direct trust=> BI relationship model was proved to be the best fit, indicating partial mediation.

3. Research model and hypotheses

The main objective of this research is to explore the complex relationship between trust, risk perception, and the intention to use of using AVs. Even though there has been considerable research into this topic, the relationship between these constructs is not evident. Based on former research and a series of in-depth interviews with car-drivers we concluded that the inconsistencies in the research results are due to the complex nature of these constructs. In the following, we present our research model, which on the one hand highlights the dimensional nature of trust and perceived risk, and on the other hand presents the relationships between these constructs.

Trust and perceived risk have attracted considerable research interest in the past few years even though the original TAM or the UTAUT model did not contain these concepts. Jing et al. (2020) mentioned trust and perceived risk as key predictor variables in the acceptance of AVs. Most research has added trust and/or perceived risk either to the original model (Pavlou, 2003; Zhang et al., 2019) or to some modified form of it (Choi and Ji, 2015). Much less research has addressed the two concepts independently of such models (Waung et al., 2021), so less attention has been paid to the direct, immediate impact of the two concepts and to distinguishing their components.

As shown in Section 2, there is no consensus among researchers on the magnitude and direction of the effect of trust and risk. For both trust and risk, there are studies that have found a direct significant effect, some that have found an indirect significant effect, and some that have found a non-significant effect of the two variables on adoption. The latter is particularly striking for risk, as several studies have concluded that risk has no significant effect on adoption (Choi and Ji, 2015; Liu et al., 2019a; (Liu et al., 2019b)). In our research, we consider it important to shed light on the background of these contradictory results and to present a model that can answer the questions that arise. Based on former research and consumer interviews, we are convinced that both risk and trust can be decomposed into well-isolated dimensions, and that the relationship between these factors reveals the depth of the impact of trust and risk.

Several authors have demonstrated that trust is a strong or even the strongest determinant of AV acceptance, directly or indirectly, but influences BI (Jing et al., 2020). Based on these results, trust directly increases AV acceptance and is a significant predictor of BI (Buckley et al., 2018; Choi and Ji, 2015; Dirsehan and Can, 2020; Liu et al., 2019a; Meyer-Waarden and Cloarec, 2021; Xu et al., 2018; Zhang et al., 2020, 2021). While these results confirm the assumption that trust is important for the adoption of AVs, most define trust as confidence in the performance of the vehicle. Very few researchers suggest that trust is multidimensional in nature and measure the effect of the different dimensions. A major contribution by Liu et al. (2019a) is that they provide evidence on the effect of social trust (trust in manufacturers and in government) in the case of AVs. On the other hand, they did not examine the effect of trust in an AV's performance dimension. Waung et al. (2021) separately examined the different dimensions of trust and differentiated not only performance and social trust, but also did a further breakdown, with the introduction of trust in manufacturers and developers and trust in rules and regulations. Interestingly, however, they do not integrate the three dimensions in one model but measure only the effect of performance trust and trust in regulation in two separate models with distinct regressions. With these considerations, we propose a model that incorporates all three dimensions of trust and measures the parallel direct and indirect effects of them.

Based on these former results, first, we propose to differentiate the three dimensions of trust and second, to measure the direct relationships between the different dimensions of trust and future behavior regarding the use of AVs.

H1: Trust in AV performance has a positive effect on intention to use AVs.

H2: Trust in AV manufacturers has a positive effect on intention to use AVs.

H3: Trust in institutions that influence rules and regulations for AVs has a positive effect on intention to use AVs.

Studies that distinguish the different types of risk came to a similar conclusion; most of them found a significant effect of one or more dimensions of risk, either directly (Zhang et al., 2019) or indirectly (Man et al., 2020; Waung et al., 2021). These results suggest that it is worth looking at risk on an element-by-element basis, as each dimension may have a different impact on intention to use AVs.

Based on former results (Zhang et al., 2019; Man et al., 2020, Waung et al., 2021)) two types of risk may have significant impact on intention to use, risk that is perceived concerning the AV's performance and in conjunction its safety, and risk that is related to the security and privacy of users' data. In this study, we incorporate these two dimensions of perceived risk and investigate their impact separately. The first dimension is performance risk, defined as the perception of the negative consequences of the AV's failure that can lead to malfunction or even accidents. The second dimension is privacy risk, defined as the perception of misuse of data and loss of control over personal data. We propose that both risk dimensions have a direct negative relationship with intention to use of AVs.

H4: Perceived performance risk has a negative effect on intention to use AVs.

H5: Perceived privacy risk has a negative effect on intention to use AVs.

An unresolved debate among researchers is the causal link between risk and trust (Jing et al., 2020; Mou et al., 2015; Siegrist, 2021). The correlation between risk and trust is evident in the case of automation and specifically in AVs. On the other hand, the direction is far more questionable, as we pointed out it in Section 2. The reason for this is the spiral process of formulating trust and risk perceptions. In the case of new technologies, especially if they are radically new, people tend to feel high risk because of the unknown effects and outputs of using such technologies. A level of initial trust is crucial for them to even think about the possibility of trying the new technology. Thus, this initial trust (Zhang et al., 2020) can reduce the risk of trying the unknown technology. In the case of the highest level of automation (Level 5), people only have a preliminary idea of how the system works and based on their level of trust (be it in the manufacturer, the performance, or the regulatory environment) they form a perception of the possible risks. If manufacturers, government, and other stakeholders manage to build trust, this perception of trust could decrease the perceived risk, and people will tend to support the new technology by using it. Use may further increase (or decrease) existing trust, which further decreases (or increases) perceived risk. This proposed process has been confirmed by a resent *meta*-analysis of Zhang et al. (2021). Based on their results, we accept the assumption that initial trust has a direct and – with the mediation of risk – an indirect impact on intention to use and we use this concept as a baseline for our model.

Until recently, researchers have not investigated how different dimensions of trust affect different determinants of risk. Although Waung et al. (2021) proved that performance risk effects intention to use AVs with the mediation of trust in performance, and privacy risk effects intention to use AVs with the mediation of trust in regulation, the factors were not included in a simultaneous equation. In our model, we propose that dimensions of trust have a direct effect on dimensions of perceived risk in the following way.

Trust in AVs' performance describes people's belief in the vehicle's dependability and safety. If AVs are trusted to be safe and efficient, the feeling of having problems with the AV itself will be lower, thus, reducing performance risk.

H6: Trust in AV performance reduces perceived performance risk.

As the social trust concept indicates (Hengstler et al., 2016; Liu et al., 2019a), trust can be directed not only toward technology but toward people and organizations who are responsible for developing the technology. One group of these organizations are the manufacturers and distributors of AVs. If people think that these organizations are trustworthy, their level of fear and perceived risk will decrease. We suggest that both types of risk may be reduced, as manufacturers are the custodians of the production of efficient and safe AVs and reliable data security.

H7a: Trust in AV manufacturers reduces perceived performance risk.

H7b: Trust in AV manufacturers reduces perceived privacy risk.

Besides manufacturers, other institutions like governments, authorities, and public and private organizations may also offer safeguards to people willing to try AVs. They may provide regulations, standards, or legal processes. These regulations and standards can apply to performance requirements as well as data security, reducing risk in performance and risk in data privacy.

H8a: Trust in institutions that influence rules and regulations for AVs will reduces perceived performance risk.

H8b: Trust in institutions that influence rules and regulations for AVs will reduces perceived privacy risk.

The proposed model based on the hypotheses is shown in Fig. 1.

4. Methodology

4.1. Research design and measurement

Our research was based on an online questionnaire. As previously described, five levels of automation are distinguished in the literature (SAE, 2018). Our questions related to Level 5, i.e., full automation, where the vehicle does everything for us. At this stage, human knowledge of driving is completely unnecessary. In the questionnaire, we gave a brief description of the technology and the level of automation. This block included the scales and their items as shown in Table 1. After an extensive review of research articles on AV acceptance, the scale items were adapted from validated scales. Of the six scales included in the final analysis, one was the outcome variable measuring intention to use AVs. The scales were based on the theory of perceived risk and trust, focusing on research of AVs. One of the most often researched dimensions of trust is the trust in AV performance, defined as the vehicle's ability to operate in a safe and efficient manner (Waung et al., 2021). The second dimension is the trust in manufacturers and distributors of AVs. We use the concept of social trust (Liu et al., 2019a) that includes both trust in manufacturers and trust in rules and regulations, but we limit the scope to the manufacturer aspect (Waung et al., 2021). As a third dimension, we investigate the effect of trust in institutions that influence rules and regulations of the development, manufacturing, and use of AVs. We use the second aspect of social trust (Liu et al., 2019a) concerning trust in government authorities and the private sector and add a new element with the inclusion of civil society as a potential influencer of rules and regulations. We use two types of perceived risk – performance (like safety risk) and privacy risk – and measure using scales from Zhang et al. (2019). Intention to use is measured in a standard way using scales from Zhang et al. (2017) and Osswald et al. (2012). The questions were rated by respondents on a Likert scale of 1 to 7, with 1 being strongly disagree and 7 strongly agree.

4.2. Participants

We used a convenience sampling technique and conducted our research online through Qualtrics. The final sample included 949 respondents from the age of 18 to 71. Demographic variables are summarized in Table 2. The average age of respondents was 30.7 years, with a standard deviation of 16.6 years. The 580 females represent 61 % of our sample. Most respondents (65.3 %) have a secondary education.

5. Results

In the analysis, we used the two-step approach of Anderson and Gerbing (1998). First, we tested the measurement model, then we tested the theoretical model. We used confirmatory factor analysis (CFA) to test the appropriateness of the scales and assess their validity and reliability. We examined the internal reliability, and convergent and discriminant validity of the scales and assessed goodness of fit of the measurement model. The proposed theoretical model was then tested using structural equation modelling (SEM). This method is capable of simultaneously revealing the relationship between all latent and observed variables in the model (Hair et al., 2014). For CFA and SEM analyses, we used SPSS Amos version 25.00.

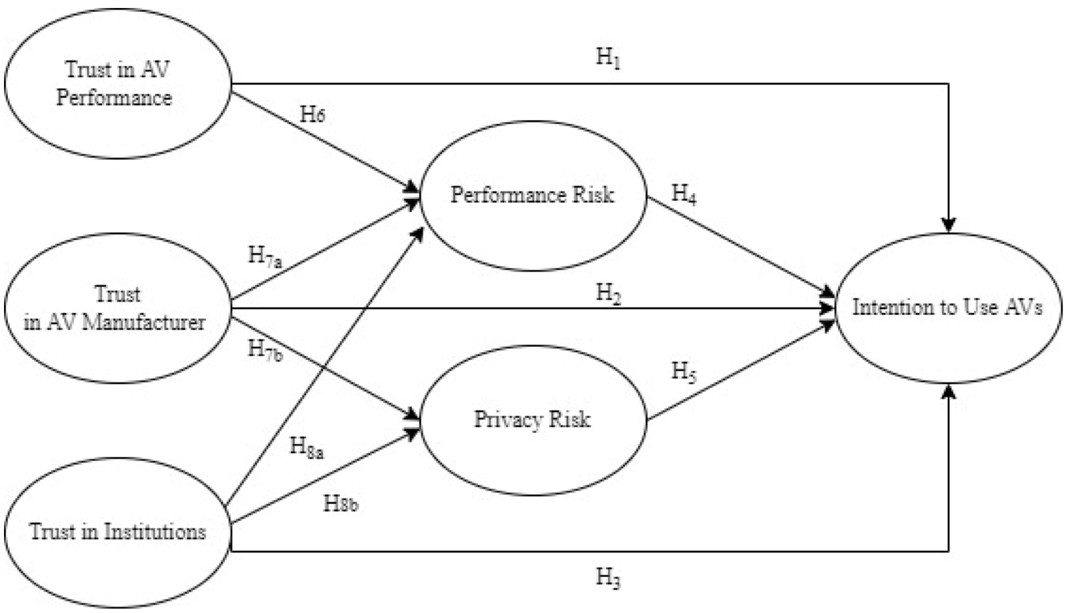

Fig. 1. The proposed theoretical model.

Table 1
Items and source of measurement scales.

Performance risk (PER)	Based on Zhang et al. (2019)
PER1	Chances are high that something will go wrong when using autonomous vehicles.
PER2	Autonomous vehicles may not perform well, and problems may occur when using them.
PER3	Considering the potential future service performance of autonomous vehicles, their use could be risky for me.
PER4	I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents.
Privacy risk (PRR)	Based on Zhang et al. (2019)
PRR1	I am worried that if I use autonomous vehicles, I will lose control over my personal data.
PRR2	I am concerned that autonomous vehicles will use my personal information for other purposes without my authorization.
PRR3	I am concerned that autonomous vehicles would not be able to guarantee the security of my personal information.
Manufacturer trust (MT)	Based on Waung et al. (2021) and Liu et al. (2019a,b)
MT1	AV manufacturers and distributors will keep their promises.
MT2	AV manufacturers and distributors will have their clients' best interests in mind.
MT3	AV manufacturers and distributors will be reliable and dependable.
Institutional trust (IT)	Based on Waung et al. (2021)
IT1	I feel assured that the government will protect me from problems that might develop from the use of AVs.
IT2	I feel confident that private industry will protect me from problems associated with the use of AVs
IT3	I feel confident that civil society will protect me from problems that might develop from the use of AVs.
Performance trust (PT)	Based on Waung et al. (2021)
PT1	I can trust that AVs can provide a robust and safe mode of transport.
PT2	Driverless cars can be trusted to carry out journeys effectively.
PT3	I trust AVs to keep my best interests in mind.
Intention to use (IU)	Based on Zhang et al. (2019) and Osswald et al. (2012)
IU1	I predict I would use autonomous vehicles in the future.
IU2	I plan to use autonomous vehicles in the future.
IU3	I will purchase an autonomous vehicle as my next car.
IU4	If the opportunity arises, I will use a self-driving car in the future.

Table 2
Summary of demographics.

Demographic variable	Value set	Frequency	Proportion (%)
Gender	*Male*	369	38.9
	Female	580	61.1
Age group	*20 years old or younger*	309	32.6
	21–39 years old	388	40.9
	40–59 years old	176	18.5
	60 years or older	76	8.0
Residence	*Capital city*	314	33.1
	County city	155	16.4
	Other city	313	33.0
	Village	166	17.5
Educational background	*Primary*	46	4.9
	Secondary	607	65.3
	Tertiary	277	29.8

5.1. The measurement model

First, we evaluated the psychometric properties of the scales using CFA and Cronbach's Alpha. We first checked the internal consistency and reliability of the indicators by linking each scale item to its corresponding latent variable and estimating the co-variances between them. Except for IT3, all factor weights were above the critical value of 0.50 and all weights were found to be significant ($p < 0.001$), supporting convergent validity. For the institutional trust scale, of the three items, the factor weight for the civil sector item was 0.3, so we removed this item from the analysis and constructed the scale from the remaining two items. The results of the corrected CFA can be found in Table 3. Cronbach's Alpha was above 0.7 for all variables, indicating a reliable measure of latent construct. Composite reliability (CR) exceeded the threshold of 0.7 for all variables (Nunnaly, 1967). To measure convergence, i.e., internal validity, we used average variance extracted (AVE) values, all of which were above 0.5 (Bagozzi and Yi, 2012). Indicators capturing the fit of the measurement model showed a good fit. We examined common method bias using Harman's single-factor method and the correlation matrix (Podsakoff et al., 2003). Exploratory factor analysis using all the items in the measurement model did not yield a single common factor, while the correlation matrix indicated that the correlation of none of the variables exceeded 0.9. The results do not suggest the presence of a common method error.

To check for discriminant validity, we used the Fornell and Larcker (1981) criterion. The square roots of the AVE values are larger than the correlations between the individual variables, supporting discriminant validity (Table 4).

Table 3
Results of the confirmatory factor analysis.

Construct	Item	Mean	Standard deviation	Cr.α	Convergent validity		
					Standardized factor loading	CR	AVE
Performance risk	PER1	4.34	1.38	0.82	0.843	0.869	0.625
	PER2	4.68	1.32		0.790		
	PER3	4.10	1.46		0.809		
	PER4	5.04	1.53		0.716		
Privacy risk	PRR1	3.43	1.57	0.94	0.846	0.917	0.787
	PRR2	3.55	1.58		0.939		
	PRR3	4.43	1.16		0.873		
Manufacturer trust	MT1	4.43	1.16	0.87	0.819	0.866	0.683
	MT2	4.71	1.16		0.799		
	MT3	4.52	1.37		0.860		
Institutional trust	IT1	3.57	1.48	0.87	0.831	0.868	0.767
	IT2	3.69	1.46		0.918		
Performance trust	PT1	4.41	1.36	0.86	0.868	0.860	0.673
	PT2	4.83	1.28		0.824		
	PT3	5.04	1.32		0.765		
Intention to use	IU1	4.23	1.68	0.95	0.917	0.953	0.835
	IU2	4.05	1.76		0.935		
	IU3	3.71	1.72		0.877		
	IU4	4.31	1.73		0.926		

Cr.α: Cronbach's Alpha; CR: Composite Reliability; AVE: Average Variance Extracted.
Model fit indexes: $\chi 2/\ df = 2.944$, $p < 0.001$; RMSEA (root mean square error of approximation) = 0.045; CFI (comparative fit index) = 0.970, TLI (Tucker-Lewis index) = 0.965.
e Variance Extracted (AVE).

5.2. Structural model assessment

We used SEM to test our hypotheses. Based on the results of the assessment of structural equations, hypotheses H1 and H2 are not accepted while H3 is. This result suggests that only performance trust has a significant direct effect on intention to use AVs (β = 0.77). Of the risk dimensions, privacy risk has a significant negative effect on intention to use (β = -0.17), while performance risk has no impact on intention to use, thus H4 was supported, while H5 was not. On the impact of trust dimensions on perceived risks, the results show that performance trust has a significant negative effect on performance risk (β = -0.58), just like manufacturer trust has a significant negative effect of privacy risk (β = -0.41), H6 and H7b are accepted. Contrary to our expectations, manufacturer trust did not affect privacy risk, and institutional trust did not affect either risk dimensions, suggesting the refusal of H7a, H8a, and H8b. The results of the hypothesis testing are summarized in Table 5 and presented in Fig. 2.

5.3. Mediation analysis

To test if there is a mediation between trust, risk, and intention to use, we analyzed indirect and direct effects using a bootstrap method (Hayes, 2013). The method allowed us to separate each indirect effect and to examine the mediating effects of both risk dimensions separately, yet in parallel. In the bootstrap analysis, we used a bootstrap sample size of 2000 with a 95 % confidence interval.

The results (Table 6) show that there is an indirect effect only between manufacturer trust and intention to use with the mediation of privacy risk. As there is no direct link between manufacturers trust and Intention to use, this is a full mediation.

6. Discussion

Most studies that investigate the adoption of AVs use TAM or the UTAUT model or some version of them. Although some elements of these models play a role in the adoption of AVs, it is important to complement the models with variables of risk and trust. While the TAM or UTAUT versions are not fully applicable to the acceptance of AVs, this research offers a new perspective by investigating the

Table 4
Results of the discriminant validity test.

	Performance risk	Privacy risk	Manufacturer trust	Institutional trust	Performance trust	Intention to use
Performance risk	**0.791**					
Privacy risk	0.482	**0.887**				
Manufacturer trust	−0.458	−0.350	**0.826**			
Institutional trust	−0.529	−0.260	0.586	**0.876**		
Performance trust	−0.673	−0.344	0.657	0.685	**0.820**	
Intention to use	−0.614	−0.364	0.468	0.574	0.813	**0.914**

Correlation matrix, where values along the diagonal (bold) are square root of AVE (Average Variance Extracted).

Table 5
Parameter estimates.

Structural relationships	Standardized regression weight	*t*-value	Result
Performance trust => Intention to use	0.77***	0.110	H1 is accepted
Manufacturer trust => Intention to use	−0.10 (ns)	0.121	H2 is not accepted
Institutional trust => Intention to use	−0.04 (ns)	0.154	H3 is not accepted
Performance risk=> Intention to use	−0.05 (ns)	0.101	H4 is not accepted
Privacy risk=> Intention to use	−0.17***	0.052	H5 is accepted
Performance trust => Performance risk	−0.59***	0.075	H6 is accepted
Manufacturer trust => Performance risk	−0.08 (ns)	0.097	H7a is not accepted
Manufacturer trust => Privacy risk	−0.41***	0.138	H7b is accepted
Institutional trust => Performance risk	0.05 (ns)	0.133	H8a is not accepted
Institutional trust => Privacy risk	0.02 (ns)	0.209	H8b is not accepted
* p < 0.05; ** p < 0.01; *** p < 0.001; n.s.- not significant			

Structural model fit indices show good model fit: CMIN/df = 1.743, p < 0.001; RMSEA = 0.057; CFI = 0.968, TLI = 0.96.

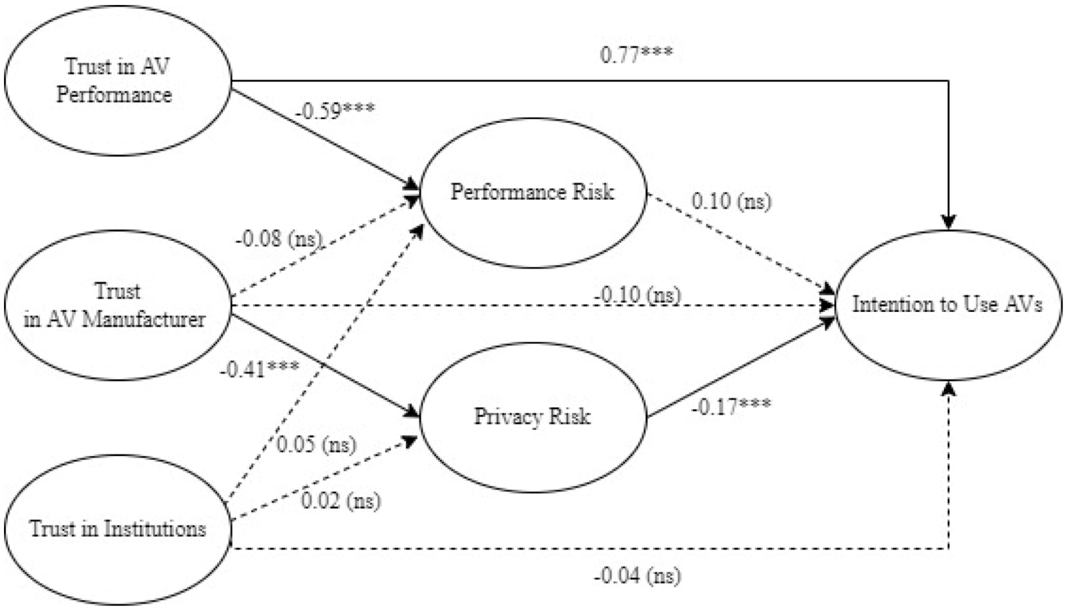

Fig. 2. Results of the structural model Dotted lines indicate non-significant (ns) relationships, ***p < 0,001.

Table 6
Mediation analysis.

Indirect effect	Standardized indirect effect	Percentile 95 % confidence intervals	
		Lower	Upper
Manufacturer trust => Performance risk => Intention to use	0.003 (ns)	-0.010	0.047
Manufacturer trust => Privacy risk => Intention to use	0.102***	0.040	0.211
Institutional trust => Performance risk => Intention to use	-0.005 (ns)	-0.073	0.016
Institutional trust => Privacy risk => Intention to use	0.000 (ns)	-0.069	0.079
Performance trust => Performance risk => Intention to use	0.033 (ns)	-0.079	0.153

2000 bootstrap samples.
* p < 0.05; ** p < 0.01; *** p < 0.001; ns- not significant.

dimensions of trust and perceived risk of using AVs.

Still in its infancy, developers and market analysts are predicting a mixed future for AV technology. Some stakeholders believe that highly automated (SAE 4–5) vehicles will be available before 2030 (Miskolczi et al., 2021), while others are highly skeptical and put its use in everyday life decades away (Siegrist, 2021; Dujmovic, 2021; Litman, 2021). Nevertheless, reports about the successes and failures of AVs are regularly in the news, in the latter case mainly accidents. For potential users, therefore, it is not primarily the actual experience that is the basis for acceptance or rejection, so it is obviously difficult to comment on the ease of use (PEOU) and usefulness

(PU). They do, however, have some idea of the reliability of the technology and the risks associated with its use, based on various types of information. Even if these perceptions are not based on reality, as users do not have their own experience of use, but on an imagined perception based on information from various sources, it is important to know about these perceptions, as they will form the basis for future decisions. If, based on available information, people conclude that these vehicles can be trusted and are safer than current technology, then their future decisions are likely to be positive. Conversely, if people conclude, based on ongoing accidents and AV crashes, that the technology is unsafe and it is risky to get into one of these vehicles, then it will be very difficult to persuade them to use them in the future when the technology is available. Overall, therefore, we believe that the investigation of trust and of risk perception are inevitable and these variables have significant role in the future adoption of AVs.

The most important contribution of this study is the in-depth examination of these two factors, and the exploration of their relationship with each other and with AVs' acceptance. In our theoretical model, we decomposed both the trust factor and the perceived risk factor into dimensions and measured their impact on each other and on future use. In our initial model, we considered three dimensions of trust and two dimensions of risk. Our research is the first to provide results on all three trust dimensions in one study using a single model. In addition, the study incorporates the two dimensions of perceived risk as the mediator between initial trust dimensions and future use intentions.

Our results suggest that our preliminary expectation that the different trust and risk dimensions would behave differently has been confirmed; this has important theoretical and practical implications.

6.1. Implications for theory

Regarding the dimensional nature and effect of trust and risk, our study yields interesting findings for theory. *First*, we distinguished and incorporated in one model three major dimensions of trust. The first trust dimension refers to the performance of the AV itself, and measures how robust, reliable, and effective it is. Performance trust is the most often used measurement of trust when studies apply only a one-dimensional construct. Contrary to this unified measure of trust, our research has shown that trust is expressed in people's minds in more diverse ways. Not only trust in the performance of the vehicle itself, but trust in the vehicle's manufacturer and the institutions that have authority to form the rules and regulations can have the basis of trust. In line with the concept of social trust (Liu et al., 2019a; Liu et al., 2019b; Siegrist, 2021) we differentiated trust in manufacturers and institutions from trust in the performance of the vehicle. In addition to the separation of trust in the vehicle, we distinguished trust in manufacturer and trust in institutions that can form rules and regulations for AVs. It is important to distinguish the different dimensions of trust when asking potential users about AVs. If we select only one of these dimensions, respondents' minds may be confused about the source of trust. While research results have already indicated that these dimensions may be distinct (Wuang et al. 2021), our study was the first to prove with a strict scale validation process using Confirmatory Factor Analysis that all three elements are valid and distinct constructs from a measurement perspective. In addition, contrary to Liu et al. (2019a) who investigated only social trust and Waung et al. (2021) who investigated only trust in rules and regulations and trust in manufacturers, we think it important to study the effects simultaneously for all three facets of trust. As long as the technology is in the development phase, trust in manufacturers and in institutions responsible for regulating the use of the technology are an important source of trust along with trust in the performance of a technology that users are not really able to assess. In addition, we can measure the impact of the different manifestations of trust on adoption only if these dimensions are separated and at the same time integrated in a unified model.

Similarly, in the case of perceived risk we distinguished separate dimensions. Based on the literature and our own understanding of the phenomenon we suggested that two main dimensions of risk should be distinguished concerning AVs: performance risk and privacy risk. While performance risk refers to the perception of risk of malfunction and the resulting accidents, privacy risk refers to the risk of losing control over sensitive data. In this interpretation security is part of performance, as in the case of AVs now. The biggest risk of the failure of technology is that it causes an accident. On the other hand, perception of missing data privacy leads to an increased risk of data leakage. Based on our results, both dimensions are valid, reliable, and distinct constructs.

Second, in line with previous research (Zhang et al., 2019; 2020), performance trust was found to have the strongest effect, with the direct effect on intention to use. There was also a strong effect of performance trust on the perception of performance risk. What is surprising, however, is that perceived performance risk does not have a significant effect on intention to use, and thus the indirect effect of performance trust through risk is not confirmed. This result suggests that the role of performance trust is a more important factor than risk perception itself. Trust has a large effect on both intention to use and risk perception, but risk perception itself has no effect on intention to use.

Third, while performance trust has a strong effect on performance risk and future behavior, it has no impact on privacy risk. Privacy risk is influenced by trust in manufacturers that only has an impact on privacy risk and not on performance risk. This result is an important contribution to the literature. When assessing trust and risk, people make a difference between their different facets. While the perception of increased trust in the vehicle decreases the perceived risk of malfunction, trust in manufacturer decreases the risk of incorrect data handling. Approached from the other perspective, trust in manufacturers does not decrease the risk of failure in the vehicle, and trust in the vehicle does not decrease privacy risk.

Fourth, while performance risk does not mediate the relationship between performance trust and future behavior, privacy risk does mediate the relationship between trust in manufacturer and intention to use AVs. In addition, there is no direct link between trust in manufacturers and intention to use, meaning that there is a full mediation. Contrary to the direct link between performance trust and future behavior intention, considered to be an affective pathway of forming acceptance (Liu et al., 2019a), the indirect relationship between trust in manufacturers and intention to use is a cognitive path, where trust influences the cognitive process of forming risk that influences the decision of accepting or refusing AVs. One potential explanation is that the vehicle itself and its performance is approached affectively, but the assessment of the data-handling problem is rather a cognitive process in the participants' judgment.

Fifth, trust in institutions has no effect in either direction. This result is remarkable for several reasons. In our research, we have highlighted and examined the role of institutional trust in addition to the other two trust dimensions. As this is the first attempt to simultaneously investigate these dimensions, our results are difficult to compare with those of other studies. Although there is not much research on this facet of trust, the results of Waung et al. (2021) prove that privacy risk has a negative impact on trust in regulation (a similar construct to our institutional trust) and trust in regulation has a positive impact on intention to use. Liu et al. (2019a) found that social trust (somewhat like our institutional trust construct) has a negative impact on perceived risk. Studies that have examined this factor at all so far have only investigated the role of this one factor, which may be quite different if the three trust dimensions are included in the model simultaneously. The method we used, SEM, allowed for a simultaneous analysis and the result may be explained by the combined analysis of the three variables. However, we consider it worthwhile to check this interpretation for future confirmation. Besides the fact that this research has a unique design, it is worth looking at the circumstances of our study to explain our specific result. We asked participants in Hungary. Hungarians are very distrustful of institutions in general and of the legal system and legislators, in particular. Based on a study in 2019 (Fülep, 2019) on a 5-point Likert scale (1 was "not trust at all") the government got 1.8; parliament 2.0; and the legal system 2.1 points. This may explain our result of having no effect of trust in institutions to any outcome variables.

6.2. Implications for practice and policy

In summarizing the implications for practitioners, we believe it is important to emphasize that both trust and risk are perceptual variables. Thus, they are not formed based on the knowledge of objective facts and figures of AV performance, but feelings and thoughts based on information from sources that are often difficult to influence. Accordingly, the implications presented herein often relate to how these perceptions can be shaped by manufacturers and other market actors (e.g., shared vehicle service providers).

For the automotive industry, trust in technology (performance) and trust in manufacturers are represented in different forms in the minds of potential users. There are two implications for this result. On the one hand, future users will not associate autonomous driving technology with a single manufacturer but will differentiate between manufacturers and the technology itself. Thus, manufacturers have their branding and autonomous technology has its own "brand"; the two are not intertwined in terms of trust. This can be important from a positioning point of view, especially when manufacturers enter the market who have not been dominant players so far. On the other hand, even if a manufacturer's reputation and brand name are strong in the 'traditional' market, it is not enough to build on this reputation in the AV market; it is necessary to address potential users' general concerns about highly automated vehicles. First of all, it would be important to provide the target group with information about what is meant by self-driving cars, and how (and in what environment) driver assistance systems can be used safely.

Our results also point to important implications for the different mechanisms of risk. As users have different perceptions of the performance and privacy risks of AVs, manufacturers need to develop different strategies for managing these risks. While emphasizing the security (accident-free) nature of AVs in their communications, as this does not reduce perception of privacy risk, the presentation of cybersecurity and data security should be focused on separately in communications. In this respect, responsibility falls on manufacturers, as our results show that potential users consider them custodians of privacy risk, i.e., they think that manufacturers can misuse their data. This is a relatively negative perception on the one hand, but also an opportunity on the other. If manufacturers integrate standards and safeguards into their operations that prevent data theft or inappropriate use of data, they can do a lot to increase adoption.

In addition, it is important to highlight the different impact of each trust dimension on the two dimensions of risk perception. Our results indicate that trust in performance does not decrease privacy concerns and trust in the manufacturer does not decrease the risk of malfunction. This result suggests that car manufacturers should make a concerted effort to design and communicate the security of AV performance. Thus, unlike in the traditional car market, we do not suggest a positioning strategy for market entry that could in any way imply a lack of security for other manufacturers, as this is likely to affect the focal manufacturer itself. Rather it is worth emphasizing the secure data handling process as a point of difference. Furthermore, the lack of significant results between manufacturer trust and performance risk may also be explained by the fact that individuals' minds are still generally attached to AVs and not to a specific brand. It is conceivable that as the first prototypes come out from each manufacturer and experience of performance increases, trust in the manufacturer will become more important.

As we already discussed in Section 6.1, the direct relationship between performance trust and intention to use is potentially an affective path, while the indirect relationship between manufacturer trust and intention to use with the mediation of privacy risk is a cognitive path. This theoretical conclusion has important implications for the communication strategy of manufacturers. The communication of the safety of AVs at present is based on the facts and figures of the different tests and special technologies that ensure safety. We are not claiming that these are not important elements of communication, but rather that this highly rational information should be complemented by more emotional cues, and communication can use more affective elements in confirming users of the safety of the vehicles. On the other hand, when it comes to privacy and data handling, it is not enough to communicate in general terms that the manufacturer is doing a lot to ensure security; more hard data is needed to build trust in the manufacturer, thereby reducing privacy risk and increasing acceptance. In this case, it is therefore not possible to avoid information on specific actions that are sufficiently tangible and transparent to users.

The unique design of our research allows that not only practitioners, but also policymakers and influencers can benefit from our results. The non-significant effect of institutional trust has one main implication: people do not trust that policymakers will actually create rules and regulations that reduce their risk perception and thus contribute to acceptance. Our implications may be of particular interest to countries where, like Hungary, trust in these institutions is very low. For countries where this level is higher, we consider it worthwhile repeating the research and interpreting the results.

What may be a more general problem is that responsibilities for highly automated vehicles are not well defined, and the legislative environment is still evolving. Basic information about the technology (what exactly is a self-driving car, what levels are involved, etc.) is also incomplete. It is likely that potential consumers do not have a clear understanding of stakeholders and responsibilities. In this context, it may be important to show how the government and the legal environment are working to create safe conditions for the user. For example, MIT's Moral Machine research is specifically looking at how machines make decisions in certain traffic situations (Awad et al., 2018). These questions need to be clarified as soon as possible so that future users have a different perception of the influence of institutions.

It is also important for policymakers to clarify the role of AVs in urban passenger transport, as they leverage the advanced infrastructure provided by large cities. A first step could be for urban and mobility planners to focus more on the regulation of AVs in urban development strategies (e.g., the SUMP – Sustainable Urban Mobility Plan framework proposed by the EU; (Transport.ec.europa.eu; 2022)). SUMPs should include a guidance to increase trust in decision-makers (e.g., naming the decision-makers, outlining responsibilities, noting how to represent consumer interests - in which zones and under what conditions the vehicle is safe to use, who can help the passenger to reduce technical and privacy risks, etc.). The emergence of artificial intelligence with AVs will also raise legal questions as to whether the car manufacturer will be at fault for any performance malfunction of the AV, or whether the vehicle technology as an entity in its own right will be at fault. Consumer trust issues will then come to the fore even more if legal entities are also delineated.

6.3. Limitations and future research

Although this study has contributions to both theory and practice, it is important to mention the limitations that may affect the interpretation of the results.

This study has been undertaken in Hungary, a country where the Autonomous Vehicle Readiness Index (KPMG, 2020) is relatively low, especially in consumer acceptance (28th place of 30 countries). While most research on AV acceptance is carried out in more advanced countries, it is worth extending research to countries with lower levels of acceptance and development. While they may be slightly behind in adoption, it is important to see how AV adoption can be developed in these countries. We also see a need to test our results in other countries and conduct intercultural studies on the differences in the influencing factors of adoption (Syahrivar et al., 2021), in particular on the role of institutional trust. Further research of institutional trust is also important to see whether the factors that we have included in our analysis can be complemented by other factors. The extent to which trust differs in public regulation and in private sector institutions (e.g. manufacturers' associations) could also be investigated.

As with any research based only on the idea of using a technology rather than its actual use, these results are primarily interpreted in the context of people who have no concrete experience of AVs but already have ideas about it. This limitation is a general shortcoming of the current attitude surveys on AVs. Experience with highly automated (SAE level 4–5) vehicles is not available (or only for a narrow segment of travelers, e.g., test users of highly automated vehicles or SAE level 4 shared mobility services, such as Waymo, Mobileye). In addition, the self-report survey is also a sampling limit for such a specific technology. Because of a lack of experience, subjects evaluate an imagined usage situation, and their perception might be influenced by several subjective factors (e.g., available information on vehicle operation, general perception of ADAS - advanced driver assistance systems).

Despite all of that, this type of research is important to reveal the initial rejection factors in customers, but it may also be worth testing the research results on those who have tried AVs in a test environment. For this, it is worth conducting consumer surveys based on vehicle testing, which could clarify the impact of the different dimensions of trust and risk on the intention to use. Unlike many current research projects, vehicle testing should be carried out in a living lab research, which would allow the variables influencing consumer intention to use in an urban environment to be refined. From this perspective, longitudinal studies can be particularly interesting.

Perceived risk and initial trust are psychological constructs that are judged subjectively by respondents. To reduce the subjectivity of the scales, it may be worth using more recently available neurophysiological tools, such as electroencephalography (EEG), eye-tracking, or functional magnetic resonance imaging (fMRI) (Venkatraman et al., 2015). Physiological measurements can only be a useful complement to standard data collection methods if subjects are able to test drive vehicles in simulated urban traffic environments. Otherwise, the objectivity of these measurements may be diminished. For all these reasons, the need for traditional self-report tests is still of primary importance in the analysis of AV acceptance.

As we were primarily interested in the trust-risk-intention to use relationship, questions on the source of trust were not included in our research. With regard to the threefold structure of trust, it would be important to examine the role of each trust factor depending on the source of the information from which potential users derive their trust in AVs.

For future studies, a further important line of research might be the investigation of how the variables under study (trust in AV manufacturer, trust in institutions, trust in AV performance) affect the intention to use AVs in relation to the mode of vehicle use (private ownership or car-sharing for a limited period). In this context, an important new institutional actor (the shared mobility service provider) may arise, toward which the different trust aspects needs to be clarified. As the reduction of private car use is an important policy in the development of urban passenger transport – shared and automated vehicles could improve urban traffic flow and alleviate current problems (e.g., road congestion and emissions from conventional transport) – extending our research in this direction could yield valuable results in the future.

7. Conclusion

When using an AV, the user should have sufficient trust that reduces the perceived risk of potential failure and misuse, thereby increasing the likelihood of future use. In our research, we have shown that trust is not one-dimensional, but has different manifestations: trust in the performance of the AV, trust in the manufacturers of the AV, and trust in the institutions responsible for regulating AVs. We also consider perceived risk in two distinct dimensions, as the user may have a perceived risk of the performance and hence security of the AV and a risk of misuse of the data that is exposed during use. Our theoretical model was tested using an online questionnaire survey filled in by 949 participants. The results of the structural assessment of the model suggest that while trust in AV performance has a direct effect on future use, trust in AV manufacturers has an indirect effect, mediated by privacy risk. Furthermore, the results suggest that trust in institutions does not influence either perceived risk or potential future use, the result of which provides scope for further investigation. The findings of this study offer useful insights not only for theoreticians but for practitioners and policymakers.

CRediT authorship contribution statement

Zsófia Kenesei: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Katalin Ásványi:** Conceptualization, Writing – original draft. **László Kökény:** Data curation, Methodology, Writing – original draft. **Melinda Jászberényi:** Supervision, Funding acquisition, Project administration. **Márk Miskolczi:** Writing – review & editing. **Tamás Gyulavári:** Data curation. **Jhanghiz Syahrivar:** Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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