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The roles of initial trust and perceived risk in public's acceptance of automated vehicles

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ABSTRACT

The purpose of this study was to explore factors affecting users' acceptance of automated vehicles (AVs, Level 3). A theoretical acceptance model was proposed by extending the Technology Acceptance Model (TAM) with new constructs: initial trust and two types of perceived risk (i.e., perceived safety risk [PSR] and perceived privacy risk [PPR]). It was hypothesized that initial trust was built upon perception factors (i.e., perceived usefulness [PU], perceived ease of use [PEOU], PSR, and PPR) and was a key determinant of AV acceptance. The validity of the model was confirmed with a structure equation modeling analysis based on data collected from 216 survey samples. Results revealed that initial trust was the most critical factor in promoting a positive attitude towards AVs, which, together with PU, determined users' intention to use AVs. Initial trust could be enhanced by improving PU and reducing PSR associated with AVs. Theoretically, these findings suggest that initial trust offers another and probably more important pathway for other factors to impact consumers' adoption of systems with uncertainty. Practically, the findings provide guidance for designing interventions aimed at improving public's acceptance towards AVs.

1. Introduction

Automated vehicles (AVs) refer to vehicles that are capable of sensing its environment and navigating without human input. The Society of Automotive Engineers (SAE, 2018) defined six levels of AVs, ranging from no automation (Level 0) to full automation (Level 5). According to this standard, AVs with conditional automation (Level 3), high automation (Level 4), and full automation (Level 5) are equipped with systems capable of monitoring the driving environment and therefore can work in automated driving mode. Compared with traditional, fully manually controlled vehicles, AVs have many advantages. First, AVs have a great potential to reduce human error-induced crashes, which account for 93% of total crashes in U.S. (Fagnant and Kockelman, 2015). In addition, with better route planning and more efficient vehicle operation, AVs can effectively reduce road congestion and fuel emission (Fagnant and Kockelman, 2015; Suresh and Manivannan, 2014). Moreover, riding in an AV frees up drivers from driving tasks and enables them to engage in their choice of leisure or productive non-driving activities (Clark and Feng, 2016; Merat et al., 2012). Finally, AVs provide a new traveling option for people unfit for driving (e.g., the elderly and the disable), which can improve the mobility of these people (Anderson et al., 2014; Duncan et al., 2015). Due to these attractive merits, automotive industry worldwide has invested huge resources in the research and development of AVs in recent years, and significant progress has been made in

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advancing and testing AV technologies in real life traffic conditions. In fact, Level 3 AVs that enable drivers not to constantly monitor the road and only to intervene when the automation system reaches its performance limit are expected to be commercially available pretty soon (Nguyen, 2017).

While AVs offer a wide range of benefits in terms of safety, energy efficiency, environment improvement and increased mobility, such benefits may not be realized until there is a large scale market adoption of AVs. However, recent surveys have shown that the public's intention to purchase or accept AVs is generally low (Abraham et al., 2017; Power, 2012; Menon et al., 2016; Schoettle and Sivak, 2014). The first survey about public opinions towards AVs conducted by Power (2012) showed that only 37% of the respondents "definitely would" or "probably would" purchase fully AVs. Another study by Menon et al. (2016) reported that 61.5% of US drivers were not likely to use AVs. It is generally suggested that the biggest barrier to AV penetration does not originate from the technology aspect, but is due to low public acceptance (IEEE, 2014; Liu et al., 2018; Noy et al., 2018; Xu et al., 2018).

To increase the public's acceptance of AVs, it is important to understand factors that have effects on AV acceptance. Some preliminary attempts have been made. For instance, it has been consistently found that young and male drivers had a more welcome attitude towards AVs and were more willing to purchase one (Bansal et al., 2016; Hohenberger et al., 2016; Menon, 2015; Nees, 2016; Payre et al., 2014; Schoettle and Sivak, 2014). Other demographic factors that contribute to a higher AV acceptance include higher income (Bansal et al., 2016; Menon, 2015), living in the urban area (Power, 2012; Shabanpour et al., 2018), tech-savvy (Bansal et al., 2016), and involving in more crashes (Bansal et al., 2016). While the above research has focused on how individual's demographics (e.g. age, income and education) were related to opinions towards using AVs, others have investigated the psychological determinants of AV acceptance by proposing and testing acceptance models (Buckley et al., 2018; Choi and Ji, 2015; Ghazizadeh et al., 2012; Kaur and Rampersad, 2018; Liu et al., 2018; Payre et al., 2014; Xu et al., 2018). Such theoretical acceptance models explain user attitude and acceptance based on the cognitive mechanisms underlying human behavior and therefore facilitate deep understanding of factors related to acceptance (Lederer et al., 2000). They are also useful for policy makers, implementers and technology developers when designing interventions to change user acceptance towards certain technology.

But still, several gaps exist in this field of research. First, the efforts to understand public acceptance of AVs are still very limited and its psychological determinants remain largely unknown (Nordhoff et al., 2016; Talebian and Mishra, 2018; Xu et al., 2018). Second, on average, only about 50% of variance in acceptance was explained by existing models (specifically, 46% in Buckley et al. (2018), 41% in Liu et al. (2018), and 55% in Xu et al. (2018)). Such explanatory power is not satisfactory given that the general explanatory power of acceptance models from information system field was around 70% (Marangunić and Granić, 2015). Third, although most of available studies have integrated trust construct into their acceptance model, its pathways (e.g. direct effect, indirect effect or mediating effect) to influence acceptance were modeled differently (e.g. Kaur and Rampersad, 2018; Liu et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018). What is the acceptable pathway for trust construct is still undetermined. Finally, survey studies have consistently reported that perceived risk was one of the most frequently mentioned reasons for not accepting AVs (Menon et al., 2016; Zmud et al., 2016a), however, many model-based studies have failed to identify the significant role of perceived risk (Choi and Ji, 2015; Liu et al., 2018).

The aim of this study was to fill these gaps by proposing and validating an AV acceptance theoretical model. We specifically focused on acceptance of Level 3 AVs given that this level of AVs is expected to be available soon. The model was built by extending a well-established technology acceptance theory, i.e., the Technology Acceptance Model (TAM), with initial trust and perceived risk. This study is among the first attempts to combine the TAM with trust and perceived risk to assess AV acceptance. Also, this study proposed that trust is the key path in shaping acceptance which mediate, fully or partially, the effect of other psychological determinants. Findings from this study are expected to provide a deeper understanding of how psychological determinants such as trust interact with each other to shape AV acceptance. From a practical view, this study will help technology developers, policy makers and implementers in providing a better quality of products and services, designing interventions to promote AV acceptance and gaining competitive advantages in the global market. The following section offers a review of related work and a detailed description about how the extended model was developed.

2. Theoretical background and model development

2.1. Theories of human behavior and technology acceptance

Many models have been developed to explain human behavior and their acceptance of new technologies. These include, but are not limited to, Technology Acceptance Model (TAM, Davis et al., 1989), Theory of Planned Behavior (TPB, Ajzen, 1991), Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al., 2003), and those expanded from the above models such as TAM2 (Venkatesh and Davis, 2000) and UTAUT2 (Venkatesh et al., 2012). These models are based on the theoretical framework that people's belief and perception of a technology can shape acceptance, with behavioral intention to use a technology (BI) and actual usage behavioral as measures of acceptance. TAM proposes that perceived ease of use (PEOU), perceived usefulness (PU), and attitude towards using a technology (ATT), are antecedents of technology acceptance. It posits that an individual's BI is determined by his/her attitude towards the technology usage. Attitude, in turn, has two primary predictors, i.e., PU and PEOU. Additionally, PEOU influences PU, and PU is specified to have a direct effect on BI (see Fig. 1a). TPB was proposed to explain human behavior in general. It posits that that individual behavior is driven by behavioral intention where behavioral intention is a function of three constructs: attitude toward a behavior, subjective norm and perceived behavioral control (PBC). Besides, PBC also has a direct effect on human actual behavior. UTAUT was developed in an effort to unify acceptance models. In UTAUT, performance expectancy (i.e., PU), effort expectancy (i.e., PEOU), social influence are direct determinants of BI, which, together with facilitating conditions, predict

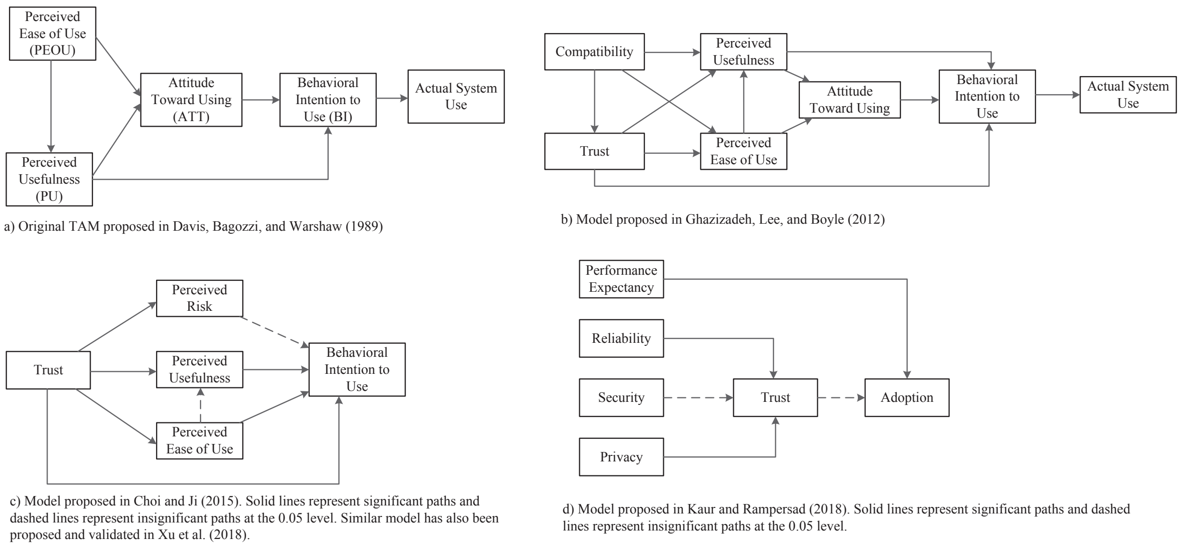

Fig. 1. The original and extended TAM models. (a). Original TAM proposed in Davis et al. (1989); (b) Model proposed in Ghazizadeh et al. (2012); (c) Model proposed in Choi and Ji (2015). Solid lines represent significant paths and dashed lines represent insignificant paths at the 0.05 level; (d) Model proposed in Kaur and Rampersad (2018). Solid lines represent significant paths and dashed lines represent insignificant paths at the 0.05 level.

actual use behavior. UTAUT has also suggested that user characteristics including age, gender, experience and voluntariness of use can moderate relationships between BI and its antecedents.

Some pioneering efforts have been made to apply the above-cited models for a deeper understanding of consumers' attitude and usage intention towards AVs. Ghazizadeh et al. (2012) integrated trust and compatibility into TAM and proposed the Automation Acceptance Model (AAM). In AAM (see Fig. 1b), the original relationships from TAM remain unchanged while trust and compatibility impact attitude and BI though PEOU and PU. Trust also has a direct effect on BI. While AAM takes a first step in providing a theoretical framework for modeling automation adoption, the validity of this model has never been verified. Choi and Ji (2015) and Xu et al. (2018) extended TAM to predict AV acceptance by incorporating trust and perceived risk (see Fig. 1c), hypothesizing that all four factors would directly impact BI; and besides that, trust could also indirectly impact BI through the perception factors. All hypothesized relationships were supported except that the direct effect of perceived risk on BI was not confirmed. Therefore, identifying the mechanisms through which perceived risk influences AV acceptance deserves further attention. The model proposed by Benleulmi and Blecker (2017) might shed some light on this question as they found that perceived safety risk could indirectly affect AV acceptance through trust construct. A more recent work came from Kaur and Rampersad (2018) where it was hypothesized that trust and performance expectancy (i.e., PU) were the two factors that directly impact AV adoption. It also hypothesized that reliability, security risk, and privacy risk were antecedents of trust factors (see Fig. 1d) and could only indirectly influence adoption through trust. This model was tested with data collected from university staffs and students but the fitness and the explanatory power of this model was not reported in Kaur and Rampersad (2018). More complex models based on general human behavior theories or interview results have also been proposed (Hutchins and Hook, 2017; Kaan, 2017), but the validity of them has not been well documented. To conclude, a review of related literature suggested development of AV acceptance models was still at its early stage. While researchers agree that trust and perceived risk are closely related to AV acceptance, they disagree in terms of the specific pathways they take to influence user behaviors.

2.2. Research model and hypotheses

To better explain user acceptance of AVs, we proposed an AV acceptance model based on TAM and the initial trust build theory. In particular, initial trust and two types of perceived risk (i.e., perceived safety risk [PSR] and perceived privacy risk [PPR]) were incorporated into the original TAM to form our model. TAM was chosen as the basic theoretical framework, because of its parsimony and effectiveness in explaining technology acceptance of various information systems (Marangunić and Granić, 2015; Tao et al., 2018) and its adaptability in the context of AVs (Choi and Ji, 2015; Kaur and Rampersad, 2018; Xu et al., 2018). The proposed model is presented in Fig. 2. In the remainder of this section, we described the rationale of variables in the model and developed hypotheses among them.

2.2.1. Behavioral intention and attitude towards usage

Behavioral intention (BI) refers to the degree to which an individual will use a technology. In the original TAM, BI mediates the effects of other potential antecedents of actual usage behavior and therefore BI is often used as the dependent variable instead of actual usage when examining the acceptance of technological systems at an early stage (Davis et al., 1989; Holden and Karsh, 2010).

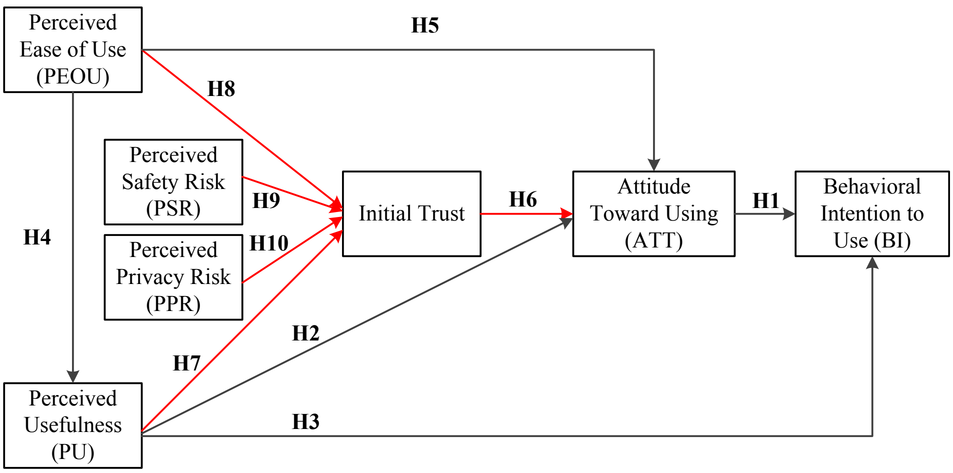

Fig. 2. The proposed AV acceptance model. The black lines represent the relationships from the original TAM; the red lines represent newly proposed relationships.

Attitude towards usage refers to an individual's positive or negative feelings towards using a technology. Numerous studies (e.g., Marangunić and Granić, 2015; Tao et al., 2018) have found that consumers with a positive attitude towards a technology tend to have a higher intention to use it. In fact, this relationship has been confirmed as the most stable one in the original TAM (Yousafzai et al., 2007). Therefore, we proposed that:

H1: Positive attitude towards AVs will increase behavioral intention to use them.

2.2.2. Perceived usefulness and perceived ease of use

Similar with the definitions in Davis et al. (1989), PU in this study refers to the extent to which a person believes that using an AV will enhance his or her performance. AVs are supposed to offer many benefits to its users such as increased safety, reduced energy consumption, and the flexibility of doing non-driving tasks, all of which might promote a positive attitude towards and a higher intention to use AVs (Choi and Ji, 2015; Xu et al., 2018; Yousafzai et al., 2007). PEOU refers to the extent to which a person believes that using an AV will be free of effort. Its relevance should not be undervalued in AV adoption given that operating AVs is a totally new experience which might require some efforts of learning. Previous studies have consistently recognized PEOU to have direct effects on PU and attitude (Yousafzai et al., 2007). PEOU can also influence BI, but usually indirectly through PU and attitude constructs (Davis et al., 1989; Subramanian, 1994). Thus, it was hypothesized that:

H2: Perceived usefulness has a positive effect on positive attitude towards using AVs.
H3: Perceived usefulness has a positive effect on behavioral intention to use AVs.
H4: Perceived ease of use has a positive effect on perceived usefulness.
H5: Perceived ease of use has a positive effect on positive attitude towards using AVs.

2.2.3. Initial trust in AVs

Trust, according to Lee and See (2004, p. 51), refers to *"the attitude that an agent will help achieve an individual's goals in a situation characterised by uncertainty and vulnerability"*. It has been identified as a key element that determines human-automation interaction (Lee and See, 2004). Distrust towards an automated system could lead to disuse while over-trust can result in misuse or abuse (Parasuraman and Riley, 1997). This has received empirical support from driving automation field. Hergeth et al. (2016) and Körber et al. (2018) found that people with higher levels of trust towards the AV system tended to monitor the automation less frequently while performing non-driving related secondary tasks. Such monitoring behavior led to longer reaction time when drivers were required to take-over control (Körber et al., 2018; Payre et al., 2017). While the above research all focuses on how trust level shapes user behaviors when interacting with AVs, it is surprising that little attention has been paid to the role of trust in determining whether consumers would accept AVs or not, although lack of trust in AV technology is the most frequently mentioned reason for not accepting it (Zmud et al., 2016b). Of the few studies that have concerned trust when predicting AV acceptance, most have reported that trust is a positive and significant predictor of drivers' positive attitude towards AVs (Buckley et al., 2018; Choi and Ji, 2015; Kaur & Rampersad, 2018). It should be noted though, given that the majority of the consumers have no chance to interact with AVs yet, trust is more precisely referred as *initial trust* (contrary to *dynamic trust* formulated during an interaction with a system, Hoff and Bashir (2015)). At the early stage of the marketization of an emerging technology, potential consumers need to engender sufficient trust in order to overcome perceptions of risk and to form a positive attitude towards it (McKnight et al., 2002). For this reason, initial trust towards AVs is particularly critical to the success of creating a favorable attitude, which ultimately determines BI to use AVs. Thus, we proposed to add initial trust into the original TAM and hypothesized that:

H6: Initial trust has a positive effect on the positive attitude towards using AVs.

Trust in automation is always relative to a task the operator wants to perform. Thus, automation must first prove itself useful to operators in order for trust to be established. The significant role of usefulness in developing trust has been confirmed in many e-commerce studies (Benamati et al., 2010; Kim and Peterson, 2017; Yang et al., 2015). However, little such research has been done in the context of driving. The only evidence came from Dikmen and Burns (2017) where it was found that initial trust towards Tesla Autopilot system was positively related to PU. The effect of usefulness on trust might have been indirectly investigated in a series of studies by Abe and Richardson who have examined how the timing of the forward collision warning influenced drivers' trust of the system (Abe and Richardson, 2005, 2006). It was found that alarms presented after the braking actions had been initiated were rated as less trustworthy compared to those presented earlier. The reduction in trust may have been the result of the late alarms' providing weaker benefits or usefulness to drivers. Based on the above evidence, it was hypothesized that:

H7: Perceived usefulness has a positive effect on users' initial trust of AVs (**H7**).

Another factor that can have an impact on consumers' level of trust is PEOU. Again, much evidence could be found in e-commerce field (Li and Yeh, 2010b; Pengnate and Sarathy, 2017). In the context of driving, the effect of PEOU on automation trust has only been indirectly investigated. There has been evidence that improving the saliency of feedback of AV system (Wang et al., 2011), providing the rationale for the feedback (Hergeth et al., 2017; Lyons et al., 2017), or visualizing the system's interpretation of current situations (Häuslschmid et al., 2017), all of which may represent a higher level of ease of use, help users build higher trust towards the automation system. Therefore, it was hypothesized that:

H8: Perceived ease of use has a positive effect on users' trust of AVs (**H8**).

2.2.4. Perceived risk

Many surveys have revealed that while respondents acknowledged the potential benefits of AVs, they have also expressed great concerns about risks associated with adoption of AVs (Menon et al., 2016; Nees, 2016; Schoettle and Sivak, 2014; Zmud et al., 2016a). The top concern was the potential safety risk (Bansal et al., 2016; Menon et al., 2016). According to Menon et al. (2016), the majority of the public extremely (36.5%) or moderately (52.6%) concerned with the safety of the AV occupants and other road users while only 7.1% did not concern at all. Worrying about safety risk due to system or equipment failure was the most frequent reason cited for being unlikely to ride in AVs (Zmud et al., 2016b). Another concern that has raised consumers' attention is the privacy risk (Bansal et al., 2016; Kyriakidis et al., 2015b; Schoettle and Sivak, 2014). Privacy risk originates from the possibility that travel data or behavioral data could be transmitted to the government, vehicle developers, and insurance companies without notice, or be used against the users or be hacked by others. Both Schoettle and Sivak (2014) and Menon et al. (2016) have reported that about one third of the surveyed US drivers reported that they were extremely worried about privacy risk caused by misuse of their AV data. Therefore, perceived safety risk and perceived privacy risk were identified as the two types of risk that were mostly likely to impact AV adoption at this stage of development.

While much evidence confirmed the important role of perceived risk, it still remains controversial in terms of the nature of the relationships among trust, risk and consumer acceptance (Mou et al., 2015). The point that has raised the most discussion is the causal links between trust and risk, in terms of the directionality of effects and antecedents. Some authors have viewed trust as a relevant antecedent of risk and suggested that a higher level of trust should reduce the level of perceived risk over time (Kim et al., 2008; Pavlou, 2003). Choi and Ji (2015) has followed this relationship in their AV acceptance model. Others have argued that risk preceded trust given that trusting parties must be vulnerable to some extent and perceive certain levels of risk for trust to become operational (Mitchell, 1999). Such relationship has also received much support from empirical studies (Hsin Chang and Wen Chen, 2008; Ortega Egea and Román González, 2011; Yang et al., 2015).

In the present study, perceived risk was modeled as a determinant of initial trust as the development of initial trust was largely based on learned knowledge about benefits and risks associated with AVs (Hoff and Bashir, 2015). That is to say, a certain level of risk is necessary for trust to be operative. Therefore, it was hypothesized here that:

H9: Perceived safety risk has a negative effect on initial trust towards AVs
H10: Perceived privacy risk has a negative effect on initial trust towards AVs.

Finally, although risk perception has been reported to directly influence users' attitude and BI in the field of e-commerce (Alalwan et al., 2016; Martins et al., 2014), in this study, no direct effect of perceived risk on attitude or BI was hypothesized for two reasons. First, a recent meta-analysis work exploring the relationships among trust, risk and acceptance suggested that eliminating the path from perceived risk to BI helped improve the model fitness. Second, Choi and Ji (2015) and Xu et al. (2018) found in their AV acceptance model that the direct effect of perceived risk on BI was not significant. Therefore, in our model the effect of perceived risk on attitude construct was fully mediated by initial trust.

Table 1
Items used to measure the constructs in the proposed model and the sources of the measurement.

Constructs	Items	Contents	Sources
Perceived ease of use (PEOU)	PEOU1	1. Learning to use autonomous vehicles will be easy for me.	Davis et al. (1989)
	PEOU2	2. I will find it easy to get autonomous vehicles to do what I want it to do.	
	PEOU3	3. It will be easy for me to become skillful at using autonomous vehicles.	
	PEOU4	4. I will find autonomous vehicles easy to use.	
Perceived usefulness (PU)	PU1	1. Using autonomous vehicles will be useful in meeting my driving needs.	Davis et al. (1989)
	PU2	2. Autonomous vehicles will let me do other tasks, such as eating, watch a movie, be on a cell phone on my trip.	
	PU3	3. Using autonomous vehicles will decrease my accident risk	
	PU4	4. Using autonomous vehicles will relieve my stress of driving	
	PU5	5. I find autonomous vehicles to be useful when I'm impaired (e.g. drowsy, drunk, drugs).	
Perceived safety risk (PSR)	PSR1	1. I'm worried about the general safety of such technology	Zmud et al. (2016b)
	PSR2	2. I'm worried that the failure or malfunctions of autonomous vehicles may cause accidents	
Perceived privacy risk (PPR)	PPR1	1. I am concerned that autonomous vehicles will collect too much personal information from me.	Kyriakidis etal. (2015a)
	PPR2	2. I am concerned that autonomous vehicles will use my personal information for other purposes without my authorization.	
	PPR3	3. I am concerned that autonomous vehicles will share my personal information with other entities without my authorization.	
Trust	Trust1	1. Autonomous vehicles are dependable.	Choi and Ji (2015)
	Trust2	2. Autonomous vehicles are reliable.	
	Trust3	3. Overall, I can trust autonomous vehicles	
Attitude (ATT)	ATT1	1. Using autonomous vehicles is a good idea.	Davis et al. (1989)
	ATT2	2. Using autonomous vehicles is a wise idea.	
	ATT3	3. Using autonomous vehicles is pleasant.	
Behavioral Intention to Use (BI)	BI1	1. I predict I would use autonomous vehicles in the future.	Gold et al. (2015) and Venkatesh and Davis (2003)
	BI2	2. I plan to use autonomous vehicles in the future.	
	BI3	3. I will purchase autonomous vehicles together with my next car.	

3. Method

3.1. Measurements

A self-administered questionnaire was designed to collect empirical data for this study. The questionnaire consisted of three sections. The first section measured demographic characteristics, including age, gender, and education. The second section asked about respondents' driving related information, including active driving experience, accident and citation record within the last three years, and preferred mode of transportation (private vehicle, public transportation, motorcycle, walking or bicycling, or others). The third section started with a brief definition of AVs at the SAE Level 3 automation, which was read as follows: "*Automated vehicles use advanced techniques such Radar, LiDAR and computer vision to sense the surrounding environment to navigate from origin to destination. Current AVs can perform most of driving tasks such as lane keeping and lane changing. However, drivers need to take over control in situations the system cannot handle (e.g. road construction)*". Following the definition was a question asking respondents whether they had ever heard of AVs prior to this survey and the sources (Internet, TV, newspaper, friends, or other ways) where they learned about AVs. Subsequently, an acceptance questionnaire included scales measuring the constructs in the proposed model (Fig. 2) was presented. The acceptance questionnaire was designed after an extensive review of the literature and adapted from validated measurement scales. Some of the measurement items were modified to reflect specific AV context and target population of interest, and for better fit for our study scenario. Modifications were made based on expert review by three human factors experts and two rounds of cognitive interviews with four graduate students. The operationalization and sources of the scale items are presented in Table 1. All items were measured with a five-point Likert-type scale ranging from "strongly disagree (=1)" to "strongly agree (=5)". A pilot test suggested that it took about 5–10 min to complete the questionnaire.

3.2. Participants

A convenience sampling technique was employed in this study. A face-to-face questionnaire survey was conducted in public parking lots in Shenzhen, one of the largest and most developed cities in China, in March 2018. Potential respondents were people who parked cars in the parking lots during our visit. Those interested in our survey first answered two filter questions. Only those with a valid driving license and had never participated in similar surveys before were invited to complete the main questionnaire. A total of 216 drivers completed our questionnaire. Table 2 summarizes the demographic characteristics and driving related information of the respondents. On average, they were 29.9 years old (SD = 6.2) and had 4.4 years (SD = 5.5) of active driving after

Table 2
Summary of demographic and driving record information.

	Frequency	Percentage
Gender		
Female	71	32.9%
Male	145	67.1%
Education		
Grade 12 or less	9	4.2%
High school graduate	25	11.6%
Bachelor's degree	155	71.8%
Postgraduate degree	27	12.5%
Weekly Driving Frequency in last twelve months		
< 1 time	89	41.2%
2–4 times	55	25.5%
5–7 times	16	7.4%
More than 7 times	56	25.9%
Accidents (in last three years)		
0	165	76.4%
1	27	12.5%
2	17	7.9%
≥3	7	3.2%
Citations (in last three years)		
0	129	59.7%
1	32	14.8%
2	20	9.3%
≥3	35	16.3%

getting a driving license. The majority of the respondents were male drivers (67.1%), had a bachelor's degree (71.8%), and had no accident (76.4%) or no citation (59.7%) within the last three years. With regard to the preferred mode of transportation, public transportation (n = 126) and private car (n = 106) were reported as the most frequently used modes. Only 8 (3.7%) of the surveyed respondents reported that they had never heard of AVs before this survey. For those who had heard of AVs, Internet was the most commonly reported media (83.3%), followed by TV (34.3%). The proportions of the respondents that leaned about AVs from friends, newspaper, and other ways were 14.3%, 6.9%, and 0.9%, respectively.

3.3. Data analysis

Confirmatory factor analysis (CFA) was applied to examine psychometric properties of the scales. Construct validity is achieved when fitness indices of the model meet with required levels. As recommended by Kline (2016), ratio of Chi-square value to degree of freedom (χ^2/df), Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA) were used as goodness-of-fit indices. In general, the higher the CFI value and the lower the values of the other three indices, the better the fit of the model. A model is considered as a good fit when $\chi^2/df < 2$, CFI > 0.95, SRMR < 0.08, and RMSEA < 0.06 (Hu & Bentler, 1999; Kline, 2016). Convergent validity is the assessment of whether multiple indicators of the same construct are in agreement (Hamid et al., 2017). To guarantee convergent validity, the factor loading of an item on its posited underlying construct factor should be significant and exceed 0.6. The convergent validity was also assessed with the Average Variance Extracted (AVE) index. An AVE greater than 0.5 is considered adequate. Discriminant validity reflects the extent to which the constructs differs from one another empirically (Hamid et al., 2017). According to the Fornell and Larcker criterion, discriminant validity is achieved if the square root of AVE (SAVE) for each of the constructs is greater than any of the bivariate correlations involving the construct in the model (Fornell and Larcker, 1981). Internal consistency was examined using Cronbach's alpha and composite reliability. To be deemed as good internal consistency, Cronbach's alpha and composite reliability should be higher than 0.7 (Fornell and Larcker, 1981; Kline, 2016; Raykov, 1997). Finally, common method variance (CMV) was investigated using the Harman's single-factor test by entering all items into a principal component factor analysis without a rotation (Podsakoff and Organ, 1986). CMV is not a problem if the single factor accounts for less than 50% of total variance.

Structural Equation Modeling (SEM) was used to test the hypotheses in the proposed model. The same goodness-of-fit criteria (i.e. $\chi^2/df < 2$, CFI > 0.95, SRMR < 0.08, RMSEA < 0.06) were applied to evaluate the fit of the proposed model. The CFA and SEM analyses were performed in EQS software (Byrne, 1994).

4. Results

4.1. Measurement model assessment

Two items in the original measurement model, PU1 and PU5, had a factor loading smaller than 0.6, and therefore were removed.

Table 3
Fit indices for the tested model.

Fit indices	Recommended value	Measurement model	Structure model
χ^2/df	2	1.68	1.67
CFI	0.95	0.96	0.96
SRMR	0.08	0.05	0.07
RMSEA	0.06	0.05	0.06

The CFA results after eliminating the two items are presented in Table 3. The goodness-of-fit indices suggested that the measurement model was a good fit to the data. All factor loadings, as shown in Table 4, were higher than the threshold of 0.6, indicating that the items were significantly related to the construct they were supposed to measure. Given that all AVEs were larger than the minimum acceptable value of 0.5 and each of the SAVEs was greater than any of the bivariate correlations involving the construct in the model (Table 5), it was concluded that the constructs maintained a good convergent and discriminant validity. Furthermore, all values of Cronbach's alpha and composite reliability were greater than the minimum required level of 0.7, suggesting that the items used to measure each construct had maintained good internal consistency. The Harman's single-factor test revealed that the single factor accounted for 38% of total variance (less than the 50% threshold), confirming that CMV was not a problem in this data set. To sum up, the measurement model showed a satisfactory reliability and validity, and was appropriate for the analysis of the structure model.

4.2. Descriptive analysis of the constructs in the model

Respondents on average considered AVs as easy to use (Mean = 3.67, SD = 0.69). Males perceived AVs to be easier to use than females (M_{male} = 3.74, SD_{male} = 0.71; M_{female} = 3.54, SD_{female} = 0.63; $F_{(1,\ 214)} = 4.05$, $p = 0.04$). The effect of education level on PEOU was also significant ($F_{(3,\ 212)} = 5.72$, $p < 0.001$). Tukey post-hoc test showed that those with an education level of 12 grades or less perceived AVs as more difficult to use than other education groups while the difference between other education groups was not significant. PEOU was positively associated with driving experience (r = 0.14, $p = 0.03$) and citation (r = 0.17, $p = 0.01$). The average rating of perceived usefulness was 3.45 (SD = 0.78). It increased with age (r = 0.17, $p = 0.01$) and citation (r = 0.16, $p = 0.02$). There was also a significant gender difference ($F_{(1,\ 214)} = 8.28$, $p = 0.004$), with males rating AVs as more useful than females (M_{male} = 3.55, SD_{male} = 0.72; M_{female} = 3.23, SD_{female} = 0.87).

Respondents perceived a high level of safety risk and privacy risk, whose average rating was 3.82 (SD = 0.78) and 3.69 (SD = 0.80), respectively. The two risk perceptions did not differ across different consumer groups. With an average score of 3.20 (SD = 0.71), AVs were rated as moderately trustworthy. The mean values of attitudes and intention to use were 3.54 (SD = 0.71) and 3.57 (SD = 0.70), respectively. Both values were higher than the average level, suggesting that respondents held a positive attitude and a good intention to use AVs. No significant demographic or driving record related effects on trust, attitude or usage intention were identified.

Table 4
CFA results, convergent validity and internal consistency.

Construct	Item	Factor Loading	Average Variance Extracted (AVE)	Composite Reliability (CR)	Cronbach's alpha
Perceived Ease of Use (PEOU)	PEOU1	0.79	0.61	0.86	0.86
	PEOU2	0.79			
	PEOU3	0.82			
	PEOU4	0.72			
Perceived Usefulness (PU)	PU2	0.60	0.51	0.76	0.74
	PU3	0.78			
	PU4	0.75			
Perceived Safety Risk (PSR)	PSR1	0.79	0.56	0.86	0.85
	PSR2	0.94			
Perceived Privacy Risk (PPR)	PPR1	0.70	0.68	0.87	0.86
	PPR2	0.95			
	PPR3	0.83			
Trust	Trust1	0.85	0.72	0.88	0.88
	Trust2	0.86			
	Trust3	0.83			
Attitude (ATT)	ATT1	0.82	0.70	0.88	0.87
	ATT2	0.90			
	ATT3	0.79			
Behavioral Intention to Use (BI)	BI1	0.87	0.82	0.93	0.93
	BI2	0.93			
	BI3	0.92			

Table 5
Results of the discriminant validity test.

	PEOU	PU	PSR	PPR	Trust	ATT	BI
PEOU	**0.61**						
PU	0.45	**0.59**					
PSR	−0.09	−0.18	**0.56**				
PPR	−0.06	−0.05	0.44	**0.68**			
Trust	0.45	0.58	−0.32	−0.10	**0.72**		
ATT	0.49	0.54	−0.25	−0.07	0.70	**0.70**	
BI	0.49	0.57	−0.16	−0.02	0.65	0.69	**0.82**

Note: Values along diagonal (in bold) are the Square Root of Average Variance Extracted (SAVE) of the constructs. Values below diagonal are the correlations between two constructs. Every SAVE is greater than any of the bivariate correlations involving the construct in the model, suggesting all constructs have achieved discriminant validity. PEOU: Perceived Ease of Use; PU: Perceived Usefulness; PSR: Perceived Safety Risk; PPR: Perceived Privacy Risk; ATT: Attitude; BI: Behavioral Intention to Use.

4.3. Structural model assessment

All goodness-of-fit indices of the model met the suggested criteria (Table 3), indicating that the proposed model was a good representation of the hypothesized relationships. Results of the estimated structure model are presented in Fig. 3, with significant paths as solid lines and non-significant paths as dotted lines. A summary of the path coefficients and the results of the hypothesis testing are shown in Table 6. Of the five hypotheses (H1–H5) derived from the original TAM, four were supported. Specifically, it was found attitude towards using AVs showed a positive effect on behavioral intention to use (β = 0.527, p < 0.001), which supported H1. PU was a significant positive predictor of BI (β = 0.335, *p* < 0.001), but not directly related to attitude construct (β = 0.075, *p* = 0.439). Therefore, H3 was supported while H2 was not. Additionally, PEOU had a significant positive effect on PU (β = 0.578, *p* < 0.001) and on attitude towards using AVs (β = 0.164, *p* = 0.021). Thus, H4 and H5 were supported.

Among the proposed hypotheses related to trust and perceived risk (H6-H10), H6 was supported since trust had a significant positive effect on positive attitude (β = 0.670, *p* < 0.001). The results showed that only PU (β = 0.604, *p* < 0.001) and PSR (β = -0.304, *p* < 0.001) showed significant effects on trust. PEOU (β = 0.146, *p* = 0.080) and PPR (β = 0.098, *p* = 0.439) were not significant predictors of trust. Therefore, H7 and H9 were supported by the data while H8 and H10 were not.

For the predicted constructs in the model, 33% of the variance in PU and 56% of variance in trust were explained (see Fig. 3). In addition, the proposed model explained 67% of variance in attitude and 61% of the variance in BI.

5. Discussion

This study proposed a theoretical AV acceptance model by extending the TAM with initial trust and perceived risk. The model

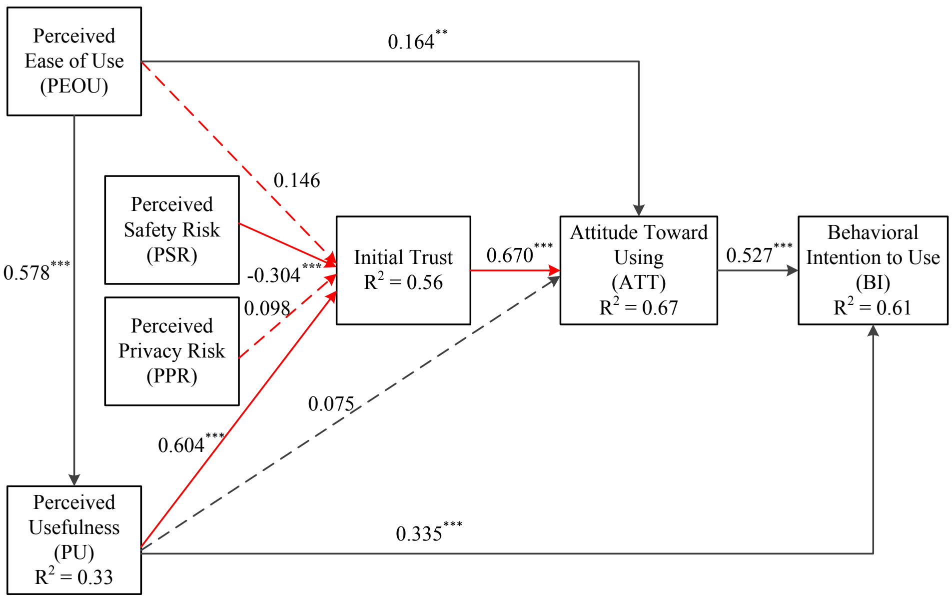

Fig. 3. Results of the structural model. The black lines represent the relationships from the original TAM; the red lines represent newly proposed relationships. Dotted lines indicate non-significant paths. *Note:* *** p < 0.001; ** p < 0.01; * p < 0.05.

Table 6
Results of hypothesis testing.

Hypotheses	Standardized Path coefficients	Supported?
H1: ATT → BI	0.527***	Yes
H2: PU → ATT	0.075	No
H3: PU → BI	0.335***	Yes
H4: PEOU → PU	0.578***	Yes
H5: PEOU → ATT	0.164*	Yes
H6: Trust → ATT	0.670***	Yes
H7: PU → Trust	0.604***	Yes
H8: PEOU → Trust	0.146	No
H9: PSR → Trust	−0.304***	Yes
H10: PPR → Trust	0.098	No

PEOU: Perceived Ease of Use; PU: Perceived Usefulness; PSR: Perceived Safety Risk; PPR: Perceived Privacy Risk; ATT: Attitude; BI: Behavioral Intention to Use.
** $p < 0.01$.
*** $p < 0.001$.
* $p < 0.05$.

argues that whether users would accept AVs or not are largely and directly determined by their levels of initial trust towards AVs, and such initial trust is built upon a combination of cognitive beliefs including PEOU, PU and perceived risks. The results provide strong support for the proposed model, with trust identified as the strongest predictor of user attitude and mediated the effects of the cognitive beliefs on AV acceptance. This study contributes to research and practice in multiple ways.

5.1. Theoretical implications

First, it was found that the role of initial trust was much stronger in predicting user attitude towards AVs than the role of cognitive beliefs. Earle and Cvetkovich (1995) interpreted trust as "a tool for the reduction of cognitive complexity" and help simplifying and facilitating decision-making process, especially in situations with risks and uncertain (Kim et al., 2008; Zsifkovits and Günther, 2015). In these uncertain situations, when consumers have to act, trust comes into play as a solution for the specific problems of risk. The trust-based decision making process has been confirmed in user acceptance of e-commerce service, with trust-attitude relationship found to be stronger and more stable than risk-attitude and PU-attitude relationships (Amin, Rezaei, and Abolghasemi, 2014; Mou et al., 2015). In the context of driving, however, to our best knowledge, this is the first time that trust was identified as the most critical antecedent in determining AV attitude. Previous related studies have either reported that the role of trust in AV acceptance was insignificant (Kaur and Rampersad, 2018), supplementary (Buckley et al., 2018) or mediated by other factors such as PU (Choi and Ji, 2015), probably due to limitations in the proposed models or the survey population. This finding suggests that trust not only influences human monitoring or operating behaviors when riding an AV (Körber et al., 2018; Payre et al., 2017), but also determines whether people in the first place would ride AVs or not. From a theoretical standpoint, the importance of initial trust in shaping user attitude towards AV was confirmed.

The second contribution to research of this study is demonstrating that initial trust could be built upon a combination of cognitive beliefs. The interacting relationships between trust and cognitive beliefs are quite complex. Technology acceptance literature from information system field tends to model trust as an antecedent of cognitive processes. However, such relationship might only be true when users have formed a stable level of trust based on information learned and interaction experienced from a multiple of sources. In other words, trust can impact user perception of a technology in the long run. But AVs are emerging technology whose potential users are still developing their initial trust and according to trust development theories, such initial trust is shaped based on users' cognitive evaluation about the reputation, the quality and the safety of the technology. Our results have provided some support to the above notion. Specifically, we found that that PU and perceived safety risk were important factors that determined initial trust. This is consistent with the automation trust model proposed by Lee and See (2004) and Hoff and Bashir (2015). According to Lee and See (2004), human-automation trust depends on performance, process and purpose of an automated system. The usefulness of an automated system is a performance-based variable (Hoff and Bashir, 2015) and therefore should be a fundamental determinant of trust. It also implies that measures for enhancing driving safety would be important and useful for consumers to develop trust in handling over the vehicle control to automation systems, which is quite reasonable considering the possible severe injuries and huge financial losses associated with road accidents.

PEOU was not identified as a significant antecedent of trust. This is kind of unexpected, considering that its close relation with trust has been reported by empirical studies in both e-commerce (Li and Yeh, 2010a; Yang et al., 2015) and automation domains (Abe and Richardson, 2005, 2006; Dikmen & Burns, 2017). A possible explanation is that the participants from previous studies had actual usage experience with the investigated system while respondents in the present study had no actual interacting experience with AVs. The lack of interaction may have weakened the relationship. It is also possible that the surveyed drivers perceived no difficulty in learning how to use AVs and therefore this factor did not contribute to enhance trust levels. The path from privacy risk to trust was not significant either, suggesting that privacy was not considered that important for Chinese when they build their trust. One possible explanation is that the potential losses associated with privacy violations in the context of driving is not as immediate and clear as those with safety risk.

The third theoretical contribution was that our results help clarifying the conflicting results on the importance of perceived risk to attitude/BI in the AV literature. While perceived risk has been frequently cited as one major concern in riding AVs in surveys (Menon et al., 2016; Zmud et al., 2016a), available AV acceptance models have failed to identify its significant effect on acceptance (Choi and Ji, 2015; Xu et al., 2018). Our results revealed that perceived risk would not directly determine users attitude towards AVs but would affect it indirectly by influencing users' level of trust towards AVs.

Finally, this study has also explored how constructs in the proposed model differ across demographic factors. It has been consistently reported in literature that elderly drivers showed less interests in AVs and were less willing to purchase one (Bansal et al., 2016; Hohenberger et al., 2016; Nees, 2016; Schoettle and Sivak, 2014). Moreover, they tended to rate AVs as less trustworthy (Abraham et al., 2017) and less useful (Menon et al., 2016). However, these findings were not reproduced in our study. The only age-related effect found here was that the perceived usefulness of AVs increased with age. This might be due to that our respondents were relatively young (age range: 20–50 years old), so they were not representative of the elderly group (> 65 years old) who had the most difficulties in accepting and acquiring new technology. Another interesting finding was that those with traffic citations tended to rate AVs as easier to use and more useful. This is expected since AVs could help drivers get rid of citations and decrease the probability of violating traffic rules.

5.2. Practical implications

Findings from this study can help vehicle developers and policy makers determine better practice for the design and implementation of AVs. Trust exhibited the strongest effects on user attitude towards AVs. This implies that creating user initial trust is the basic and significant part of AV promotion. One possible strategy, according to our model, is to decrease perceived safety risk. Therefore, it is suggested that manufacturers need to explain how a car would protect passengers when crucial systems fail, and when possible, even make their safety algorithms and data available to the public. Moreover, policymakers should work closely with academics and manufactures to set safety rules and ensure developers strictly follow the safety standards. Another possible strategy to enhance trust is to improve users' PU. This can be achieved by advertising benefits of using AVs, such as relieving congestion and increasing mobility. Manufacture can also consider offering users opportunities to directly experience AVs as such experience is effective in improving PU (Hartwich et al., 2018; Xu et al., 2018). PEOU was identified as a significant positive predictor of user positive attitudes. It implies that AV designers should not ignore the efforts required to operate AVs as suggested in previous surveys. Rather, they should try to reduce the complexity and increase the clarity of interaction between human and the automation systems.

5.3. Limitations of this study and future work

The results of our study need to be interpreted in consideration of several limitations. One limitation is that subjective measure of trust and acceptance might not represent objective behaviors (Perkins et al., 2010). Behavioral indicators (e.g. engagement in secondary-tasks) and physiological indicators (e.g., heart rate, Waytz et al., 2014) can be used in future studies to measure trust level. Another limitation is that the majority of the respondents did not have actual experience of AVs and trust discussed in this study was the initial trust built upon respondents' knowledge acquired from Internet or TV. The level of trust and its antecedents would change in the future, with users' more familiarity with the system (Koustanaï et al., 2012) and a deeper understanding of how the system works (Balfe et al., 2018). Therefore, longitudinal studies are recommended to further clarify how trust and its role in user acceptance evolve after users have more interacting experience with AVs. Moreover, future studies should explore the role of other factors such as reliability, perceived cyber-security risk, liability concerns, and driving pleasure on acceptance. Finally, findings were built upon level 3 AVs with a dominant feature that vehicle control can be returned to human drivers under some situations. The relationships among the constructs of the proposed model might change in the context of higher levels where take-over-control is not necessarily a part of AV operation and deserve exploration by future studies.

6. Conclusions and implications

By incorporating initial trust, perceived safety risk and perceived privacy risk, this study has proposed and empirically tested an extended TAM to understand consumers' attitude and behavioral intention to use AVs. To our best knowledge, trust was for the first time identified as the most critical factor in promoting a positive attitude toward AVs. From a theoretical perspective, this implies that the relations in the original TAM are not the only mechanism in terms of how acceptance behavior is developed in the context of automation systems. The construct of trust offers another and probably more important path for other factors to impact consumers' adoption of systems with uncertainty. From a pragmatic perspective, this finding suggests that to promote public's acceptance of AVs, related organizations should target on improving the trustworthiness of AVs. This can be achieved by reducing system flaws and incorporating safety enhancement functions given that perceived safety risk was found to be negatively related to users' initial level of trust. Besides, initial trust can be enhanced if consumers find AVs to be useful. Therefore, car manufacturers and government can advertise the benefits of using AVs, such as relieving congestion and increasing mobility, to increase consumers' awareness of the usefulness of AVs. Finally, the role of PEOU should also be emphasized considering its positive role in building a favorable attitude towards AVs. This implies that a well-designed interface that requires little effort to understand and causes no confusion should be useful to facilitate public's acceptance of AVs.

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